Persistent Lexical Entrainment in HRI

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ABSTRACT

In this study, we set out to ask three questions. First, does lexical entrainment with a robot interlocutor persist after an interaction? Second, how does the influence of social robots on humans compare with the influence of humans on each other? Finally, what role is played by personality traits in lexical entrainment to robots, and how does this compare with the role of personality in entrainment to other humans?

Our experiment shows that first, robots can indeed prompt lexical entrainment that persists after an interaction is over. This finding is interesting since it demonstrates that speakers can be linguistically influenced by a robot, in a way that is not merely motivated by a desire to be understood. Second, we find similarities between lexical entrainment to the robot peer and lexical entrainment to a human peer, although the effects are stronger when the peer is human. Third, we find that whether the peer is a robot or a human, similar personality traits contribute to lexical entrainment. In both peer conditions, participants who score higher on "Openness to experience" are more likely to adopt less conventional terminology.

1. INTRODUCTION

It is known from numerous studies that when people talk, they influence each other's speech patterns, that is, speakers converge on similar linguistic features [1, 11, 14, 25, 26, 35, 36]. Convergent phenomena are known to occur with respect to pronunciations, speech rate, and sentence structure, among other domains. In the current study, we are particularly interested in word choice. Even though in a conversation, speakers have a wide range of words to choose from to refer to the same entity, once one speaker chooses a particular reference term, his or her interlocutors tend to follow suit by using the same term [11, 13]. The tendency for speakers to imitate one another's vocabulary choices is known as **lexical entrainment**.

A variety of studies have shown evidence that people adjust their speech when interacting with machines, including robots and speech recognition systems [4, 10, 27]. However, it is important to note that, in general, speakers may have various reasons for adjusting their speech. For instance, speakers may shift their language output toward that of interlocutors they hold in high regard [16], suggesting that convergence is motivated by a desire for social solidarity or prestige. On the other hand, speakers may adjust their speech simply to make it easier for their interlocutor to understand. Note that speakers might be especially motivated by the second mechanism – easing comprehensibility – if they have a poor opinion of their interlocutor's language abilities. Such considerations cause people to make particular adjustments when addressing a non-native language speaker, such as speaking slower and louder, and using simplified vocabulary and grammar [5, 12, 28, 32].

Indeed, Branigan et al. [8] observe that much of the existing research on linguistic accommodation to machines may, in fact, represent this latter kind of speech shift – motivated by an attempt to be understood by a device that is far from an expert in one's native language. Such could be the case with previous robot research by Iio et al. [17, 18]. In that study, lexical entrainment is measured only during the course of interaction with a robot interlocutor. For purposes of facilitating communication (and completing the assigned experimental task), it is only natural to switch to terms the robot already uses. If switches are made solely for immediate, practical purposes, they may very well not persist beyond the limited scope of interactions with a robot. In contrast, it is known that the effects of human-to-human interactions can be extended to new conversation partners, and they play a role in language change over time [13].

In this study, we thus test carefully for both similarities and differences between human-robot lexical entrainment and human-human lexical entrainment. We set out to investigate lexical entrainment to robots, such that we can rule out mere communicative facilitation, in contrast with previous research [17, 18]. Thus, in our experimental design, we measure lexical entrainment effects which linger after the interaction phase is completed. Moreover, we will compare our lexical entrainment results with a robot peer against a

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control condition, in which a human actor takes the place of the robot.

It is anticipated that it may be challenging to observe shifts in word choice which are not motivated by communicative facilitation. We note, for instance, that in previous research based on Solomon Asch's conformity studies, participants failed to converge to robots in their choice of English past tenses when there was no communicative incentive to do so [3, 7]. Thus, in an attempt to maximize the influence of robots, we ask participants to engage in a collaborative exercise with robots, to observe if this setup will encourage them to accept the robots as social peers. The collaborative exercise is based on a navigation task that requires interaction and teamwork. In this task, the participant and the robot have to help each other navigate on a field, such that one team member needs to move on the field, while the partner has the required map.

Our collaborative exercise is designed to encourage the participant to develop a sense of in-group belonging with his/her partner (whether robot or human). We prompted each participant/peer pairing to be competitive against other teams performing the tasks, with respect to the amount of time required to finish. This team-building approach creates a situation where the the participant and robot/actor are part of the same in-group, and define themselves against competitor out-groups [22]. The social effects of in-groups are well-documented; individuals are known to trust in-group members more than out-group members [24, p. 695] [29, p. 335]. Furthermore, the effect of in-group/out-group membership can be observed between humans and robots[22]. People are more likely to favour answers from their own in-group than from the out-group. The effect of in- and out-groups can also be found in linguistic settings [34]. Unger et. al. find that participants in an in-group will mimic their interlocutors more than if the interlocutor is from an out-group.

1.1 Research questions

The aim of our study is to see whether social robots can influence human language beyond the time of interaction. Furthermore, we want to see how social robots compare to humans in the same task. With this in mind we built the interaction so as to test the following research questions:

1. Is it possible for a social robot to prompt lexical entrainment that persists even after the interaction with the robot is complete?
2. Does the influence of social robots to humans align with the influence of humans on each other? Is the effect stronger in one condition compared to the other?
3. What role is played by personality traits in lexical entrainment to robots, and how does this compare in lexical entrainment to other humans?

2. STIMULUS SELECTION

Before we could start experimenting with lexical entrainment, we had to find image stimuli on which to influence and test the participants. Since the items need to be used as visual reference points, we obtained highly imageable words from the MRC Psycholinguistic Database [37]. We chose ninety-nine items from the MRC list, and sought corresponding images to serve as simple, schematic prompts that would be visible within a complex map grid. We collected icon images using the www.flaticon.com database, limiting our results to images which are licensed under the Creative Commons Licence or Flaticon Basic License. Example images appear within the map layout of Fig. 2. The next step was to generate a list of possible terms for each of the ninety-nine items. To do so, in a pilot study we asked twelve volunteers to generate as many words as possible for all ninety-nine icons. For each icon we sorted the responses to determine which terms are most likely understandable by future participants.

The final step was to finalize a set of eighty icons to be used in the experiment. During this selection process we avoided the inclusion of any icons that overlapped in their candidate terms to avoid cross-item priming effects. For example, both a work boot and a deck shoe might prompt "shoe", and thus one of these icons would be disqualified. An illustration of an icon plus example candidate terms can be seen in Table 1.

Ultimately, the eighty selected icons are split into two halves: 40 items are designated as distractor items, and 40 are designated as stimulus items. For the distractor items, it will be the participant's job to provide directions to his or her navigation partner. For the stimulus items, it will be the navigation partner's job to direct the participant; it is thus on these items that peer influence will be exerted. Distractor items are used to distract the participant from the real experiment, and to give him/her the impression of a reciprocal collaboration.

The baseline naming study discussed above was used to establish an "Expected Term List" for the 80 icons used in the experiment, containing all the words that volunteers used as names for the items. This list is used as a database during the experiment, to allow for smooth interactions in response to participants' verbal responses. Moreover, based on the Expected Term List, for each of the 40 stimulus icons, we selected two top candidates (the "Preferred Pair") as options available to the participant's (robot/actor) peer, to influence the participant over the course of the experiment.

Icon	Candidate Term
	• Alligator • Crocodile • ...
	• Soldier • Terrorist • ...

Table 1: Excerpt of icons plus terms from the Expected Term List

3. EXPERIMENTAL SETUP

The basic experimental design follows a pre-/main-/post-task setup. In the pre-task, we recorded what the participant named the items we presented to them, and used this information to customize the influence exerted during the main task. In the main, collaborative task, the robot/actor peer introduces new words for some of the items, i.e., in selected instances, the peer's terms differ from the participant's pre-task terms. Finally, in the post-task, we again record what the participant calls the same icons. The influence of the main task on the post-task is then analyzed.

As an important element of this experiment design, we wanted to see how robot influence compares to human influence. Thus, some participants were paired with a robot partner – a robot with a synthesized female voice, which we introduced as "Helen". Participants in a different condition were paired with a female actor (also named "Helen"). Our goal was to keep the two conditions as similar as possible, thus limiting the change only to body shape (robot vs. human), but using the same voice in each case. This, of course, created the problem of having to provide an excuse for why the actor has a synthesized voice. We made a decision to tell the participant that they are in a control condition, and that it was necessary to use the same, artificial voice that we were using with a different group of participants.

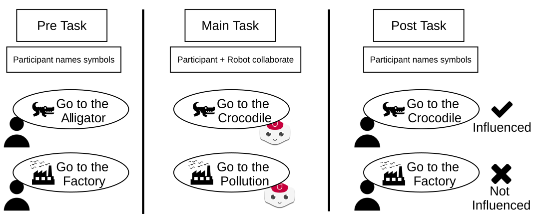

Figure 1: Shows a successful and non-successful robot influence comparing between the pre- and post-tasks.

The context in which participants are tested is a map navigation task. The general form of this task works as follows: the two participants have both a map, in which stimulus icons designate individual navigation points on the map. There is only one correct route to navigate from one side of the map to the other. To make it a collaborative task, the two participants hold each other's map, such that teamwork is required to navigate successfully. The goal is to see if a newly introduced term from one participant is picked up by the other.

To control what the robot/actor does and says during the experiment we use a hidden operator, in a Wizard-of-Oz paradigm. The operator's job is to control what the robot/actor says during the experiment and to record the participant's selections. To make sure conditions are comparable to each other, the operator has to strictly follow a predefined script.

3.1 Implementation

This section is intended to give, first, an overview of how the navigation task is implemented from the participant's perspective, and second, how this task is implemented from the operator's perspective. Moreover, it will give an overview of how the experiment's scenario is presented to the participant as a collaborative task.

3.1.1 Map task: The participant's job

In the navigation task, each participant (also the actor/robot) sees a map on a screen in front of them with a virtual avatar representing either themselves or the partner. The map itself is composed of hexagonal tiles with stimulus icons on them. Some of these tiles are yellow bordered, indicating that this is a safe path/tile to step on (see Figure 2). The goal is to navigate the avatar from tile to tile (step by step) by only stepping on the yellow bordered tiles.

Figure 2: Excerpt of the game board. The yellow bordered hexagon field show the correct path. The red arrow highlights the avatar which represents the participant or robot/actor.

Since we have two different types of tasks (pre-/post-task and main-task), the way to move the avatar on the map is slightly different. The difference depends on if the participant is alone in the room or is collaborating with the robot/actor. For the pre-/post-task the participant will see his/her own avatar on the map and will also see his/her own correct path. For the main-task, the participant will see his/her own avatar on a map without the correct path, and – on a different map – the partner's avatar, with the correct path highlighted.

The actions the participant has to take for the two types of tasks work as follows. In the pre-/post-task the participant is presented with a marked map; no navigational partner is present, so for each response, the participant merely says aloud the name of the icon on the next highlighted hexagon. In the main-task the participant and the robot/actor take turns. If it is the participant's turn to move, the robot/actor will tell the participant what icon to move to next. In this case the participant will use the computer mouse to click on the map space with the appropriate icon. If it is the robot's/actor's turn to move, the participant will tell the robot/actor what icon to move to next. Turn by turn, each participant and robot/actor character will move closer to the end of the map until the task is over.

3.1.2 Map task: The operator's job

While the participant works through the pre-/main-/post-tasks the operator's job is to perform the speech-to-text recognition that enters participant responses, and to initiate system responses at context-appropriate times. The specific responses of the robot/actor are determined by the participant's pre-task answers and a pre-set script, as described below in Section 3.5.

While entering participant responses, the operator has available a set of likely names for each item (the "Expected Term List") to allow the experiment to proceed smoothly. During the pre-/post-task, as the participant provides the name of each item, the operator simply clicks on the appropriate term from the Expected Term List. If the participant uses a term not on the list, the operator simply records it as "OTHER."

During the main, collaborative task, the actions the operator take are slightly different, as follows. If the participant uses a word from the Expected Term List, the operator will click this term's button, which will prompt the robot/actor to move to the appropriate icon on the map. Additionally, the robot/actor will say "I'll move to the [word]". In case the word is not in the list, but it is a correct term for the given icon, the operator can click on the OTHER button. This will also make the robot/actor move forward but will prompt the robot to say "OK".

3.1.3 Scenario

Linguistic research shows that social connection is needed to influence language [33], and passive exposure to speech (especially robot speech) may be insufficient to change behaviour [3, 7]. Thus, we set out to devise a collaborative experimental task which would foster a sense of social connection with a partner. Moreover, we encouraged the sense that the participant and their robot (or actor) peer formed an in-group, and could be contrasted against out-groups (see Section 1).

Toward this end, we presented participants with the map described above, and described the following scenario: *Both of you are lost in the middle of the Forest of Random Things. You have to navigate across the landscape to reach the edge. You need to follow the yellow bordered tiles, as you did in the previous task. It is important to only step on the yellow bordered tiles, and not on the other tiles.*

You and your partner must collaborate by telling each other which hexagon to travel to next. The trick is that each of you has the map that your partner needs. You must help each other navigate, and have to take turns. You can only take one step before the other one can take a step. For this task, you will use your mouse to click on the tile that your partner tells you to move to, rather than moving your own character, and the same applies to your partner.

You and your partner are a team, and you are competing against other teams who will be doing the same task. The goal is to be faster than other teams. Try not to make mistakes, so you can travel to the end of the map faster than other teams.

3.2 Procedure

The series of tasks for an experiment participant proceed as follows. (See Figure 3). First, the participant is welcomed by the operator into the experimental room where s/he is asked to take a seat. At this stage, the operator gives a short introduction about the general tasks and asks the participant to sign the consent form. Next, the operator start a tutorial level of the pre-task. After the participant becomes familiar with the setup and knows how to use the speech-to-text system to navigate around the map, the operator loads the pre-task. During the pre-task the operator moves to his/her desk where s/he is invisible to the participant and waits until the participant finishes the pre-task. Next, the operator asks the participant to fill out a demographic survey and complete a personality test, while the operator brings in the robot/actor. Before the robot/actor and participant proceed to the main-task, the operator will introduce them to a scenario (see above). After that the operator loads the main-task tutorial, so the robot/actor and the participant can practice the task. As soon as they are ready, the operator loads the main-task. After about ten minutes, the main-task is over and the operator will leave the room with the robot/actor. After the operator comes back, he/she loads the post-task and asks the participant to finish it. At the end, the participant gets debriefed and received $10.

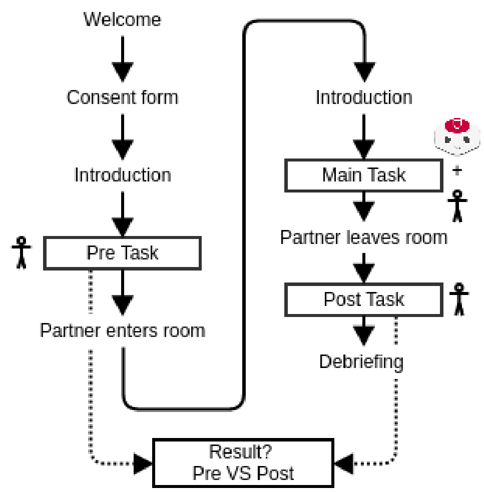

Figure 3: The experimental procedure a participant will go through.

3.3 Apparatus

The apparatus consists of a table with two monitors on it, an Aldebaran NAO robot or actor, a microphone and an extra computer. The computer was used to control the recording, run the map system and to start/control the experimental conditions. The participant and the robot/actor are positioned opposite to each other. The angle of the monitors is set in a way that the participant and the robot/actor can see one another's faces; however, their monitor displays are not visible to each other.

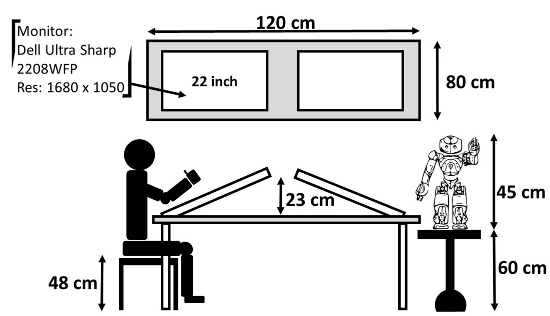

Figure 4: Schematic depiction of the physical setup with accurate physical dimensions.

3.4 Participants

Forty participants were recruited at the University of Canterbury, including students and staff. Subjects received a voucher in the amount of $10 NZD for participating. All participants were native New Zealand English speakers. The average age of our participants was 23.7 years, whereas the oldest was 45 years and the youngest was 18 years. 55% of the participants reported themselves as male and 45% of the participants reported themselves as female. Out of the 40 participants, 20 were assigned to the robot-peer condition and 20 to the human-peer condition.

3.5 Map task: The computer's job

The responses generated by the robot/actor are based on a script in which we define the behaviour the robot/actor should have. This behaviour comes partially from the pre-task, which establishes what term the participant used at the beginning of the experiment, and partially from an individual initialization, which defines (a) the random pre-assignment of influence strategies for each item (explained below), and (b) the random sequence of stimulus items. Please refer to table 2 for an excerpt from one set of random initial conditions. This same setting would be implemented with two different participants: one in the robot peer condition, and a matched participant in the human peer condition.

The influence strategies are designed so as to be variable for each participant: on some items, the navigation term used by robot/actor should CHANGE from the participant's pre-task term. On other items, the navigation term should MATCH the pre-task term. The balancing of CHANGE and MATCH robot behaviours (20 items of each, for each individual condition) is intended to allow for statistical comparisons of behaviours under different circumstances, that is, when new terms are introduced by the peer, and when they are not. Moreover, matching the participant's pre-task term some of the time avoids making the peer's vocabulary manipulation too obvious.

Since responses in the experiment are open-ended, it is impossible to anticipate every response by participants, and matching (or systematically changing from) these responses is potentially quite complex. On the other hand, in many cases the same responses are volunteered by a large number of participants. We elected to draw on our experiment's pilot study (see Section 2) to provide the robot/actor a repertoire of two possible terms to choose from (the "Preferred Pair"). This more controlled approach was felt to be preferable to presenting participants with an open-ended set of prompts. The CHANGE/MATCH designations were thus implemented as follows. If, on a particular experiment run, an item is designated as a MATCH, and the participant's pre-task answer is in the Preferred Pair (e.g., "crocodile"), the robot's/actor's navigation term is also "crocodile"). If the item was designated as a CHANGE, the robot/actor will answer with the other item from the pair ("alligator"). If the participant's pre-task answer is not one of the Preferred Pair items, it is necessary to choose at random one of the Preferred Pair items for the robot's response. Note that this approach means that some items originally designated as MATCH items, are effectively treated as CHANGE items. However, this approach still results in the robot/actor matching the participant's original selection approximately one-third of the time.

4. RESULTS

4.1 Peer condition comparisons: Matching specified targets

To study the effects of peer influence on post-task responses, we designated a semi-arbitrary set of response terms as "targets". In the present analysis, we label as the "target" the less likely of the two available peer responses, as determined by the pre-task (across all participants). [1] The analysis thus measures, as its dependent variable, whether or not the participant's post-task response was the target response.

Table 3 shows raw numbers of how often, in each peer condition, the participant already matched the target of interest at the pre-task stage. In the human-peer condition, participants' pre-task answers matched the target 10.31% of the time, compared with 12.10% for participants in the robot-peer condition. Calculating an average (by participant) target-matching score for the pre-task reveals that there are no significant differences between the two peer conditions; ($t(35.16) = -1.240$, $p = .22$).

Moreover, the peer influence during the navigation phase is also matched across the two peer conditions. That is, there are no cross-condition differences in how often the (robot, human) peer matched the target. The raw counts are shown in Table 4. In sum, robot peers matched the target items 50.03% of time, compared with 49.49% of human peers. Analysis of the average target-matching score (grouped by participant, but focusing on the peer's behaviour) reveals that there are no significant differences between the two peer conditions in the navigation phase: ($t(37.50) = 0.234$, $p = .82$).

Since the tendency to match target items – in the pre-task as well as the navigation phase – is matched across the two peer conditions, we are justified in making comparisons across these peer conditions in the post-task results.

Indeed, differences are evident between the post-task responses between the robot and human peer conditions. Table 5 shows the raw numbers of post-task matches to the target items, by condition. In the robot peer condition, participants matched the target 24.04% of the time in the post-task, as compared with 32.07% of the time in the human peer condition. Comparing participant-specific average target-match scores shows that there is a significant difference in the post-task ($t(36.30) = 2.532$, $p = .016$).

4.2 Analysis 1: Effect of the navigation peer, and differences by peer condition

The foregoing analyses shows that there are broad differences in behaviours between the human and robot peer conditions. However, we now perform more fine-grained analyses to explore the experiment dynamics in detail. First, we use logistic mixed-effects regression to investigate whether (a) a significant difference exists in post-task responses between human and robot conditions, as suggested above, and (b) whether, in *both* conditions, the influence of the navigation partner is, in fact, significant.

In our regression modeling, we include several predictors as categorical variables. First, as a between-subjects variable, we note the PEER CONDITION (robot or human). As an additional variable, we note whether the participant's preferred response (during the pre-task) matched the target. Inclusion of this predictor (PRE-TASK_ MATCH_ TARGET) is necessary to account for the fact that some pre-task responses already match the target (see Table 3). Finally,

[1]Note that the present analysis also works in a separate analysis, if the more likely response is chosen as the designated target.The designation of one target vs. another is not essential.

item	Navigator	PreferredTerm1	PreferredTerm2	change
thief	robot	robber	thief	CHANGE
axe	participant	NA-distractor	NA-distractor	NA-distractor
dog	robot	dog	wolf	MATCH

Table 2: An excerpt of an input setting file for one participant.

	human condition	robot condition
does not match target	696	684
matches target	80	94
TOTAL	776	778

Table 3: Breakdown of matches to target term: subject's answer during pre-task.

	human condition	robot condition
does not match target	388	393
matches target	388	385
TOTAL	776	778

Table 4: Breakdown of matches to target term: peer choice during interaction (main task).

the variable PEER_ MATCH_ TARGET notes whether the peer (whether robot or human) matched the target term during the collaborative task (see Table 4). This variable is the crucial indicator of the presence or absence of influence by the peer. The dependent variable is a TRUE or FALSE variable, corresponding to whether the participant used the target word during post-task responses.

We performed logistic mixed-effects regression, incorporating random intercepts for participants and items [19]. The model also incorporates random slopes: for each participant, the slope is allowed to vary for PRE-TASK_MATCH_TARGET and PEER_MATCH_TARGET, and for each item, the slope is allowed to vary for PEER CONDITION. The resulting model is summarised in Table 6.

The model indicates the following. First, matching the target in the pre-task (PRE-TASK_MATCH_TARGET) is a significant predictor of matching in the post-task. If a participant was already using the target word in the pre-task, he or she is likely to continue doing so in the post-task. This result is unsurprising, but it represents a factor that needed to be controlled to verify influence of the peer.

Secondly, as a general main effect, the peer's use of the target term in the navigation phase (PEER_MATCH_TARGET) is a significant predictor of matching the target during the post-task. Thus, in both conditions, the robot or actor's choice of the target terms was likely to prompt use of this term by the participant, after the peer interaction was completed. This main effect provides evidence of significant influence by the partner, in *both* robot and human conditions.

	human condition	robot condition
does not match target	528	591
matches target	248	187
TOTAL	776	778

Table 5: Breakdown of matches to target term: subject's answer during post-task.

Thirdly, the influence of the navigation partner is stronger overall in the human condition, compared with the robot condition. This is evident from the interaction between PEER CONDITION and PEER_MATCH_TARGET. This interaction is shown in the effect plot of Figure 5. Note that the peer condition (robot or human) is not significant as a main effect in this model. This is not surprising because the data for this model includes both cases where the peer did, and cases where the peer did not, introduce a new term during the navigation task. The difference between conditions is evident only when the peer could have conceivably prompted a switch to the target item, i.e., from the PEER CONDITION and PEER_ MATCH_ TARGET interaction.

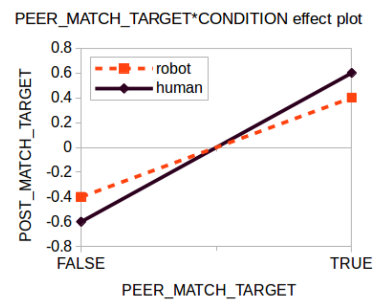

Figure 5: Interaction plot from the model in Table 6

4.3 Peer condition comparisons: Switching to peer's term

The foregoing analyses examine all participant responses in the post-task, including cases where the peer did not exert any relevant influence on word choice (that is, because the participant was already using the same term in the pre-task, and thus could not switch). We may perform even finer-grained analyses by focusing only on responses where the participant had a meaningful opportunity to change to the peer's word choice.

Thus we may ask: focusing on instances where the peer introduces a term that is new to the participant, how often does the participant switch to the new term? We consider this question, first of all, as an average measure for each participant. This measure is summarized in Figure 6, which shows density plots of participant aggregates (grouped by peer condition). This plot shows that overall, clearly it is more likely for participants who are paired with a human to switch terms, as compared to participants paired with a robot peer. In the human-peer condition, participants switch to their peer's term on 61.12% of all opportunities to do so (across participants, SD = 20.53). By comparison, participants switch 38.92% of the time to a robot peer's term (SD = 18.65). This difference is statistically significant ($t(37.65) = 3.58$, $p < .001$). However, it is notewor-

	Estimate	Std.Error	z value	pval
(Intercept)	-5.04	0.59	-8.51	$< .001$
PRE-TASK_MATCH_TARGET	3.15	0.48	6.62	$< .001$
PEER_CONDITION = robot	0.84	0.63	1.34	0.18
PEER_MATCH_TARGET	5.23	0.69	7.57	$< .001$
CONDITION =robot* PEER_MATCH_TARGET	-1.83	0.82	-2.22	0.03

Table 6: Regression model summary.

thy that much cross-participant variation exists within each condition, and a considerable overlap exists across the two conditions; see the double-shaded region in the middle of the density plot. That is, there are some participants in the robot-peer condition who switch terms more often than some participants in the human-peer condition.

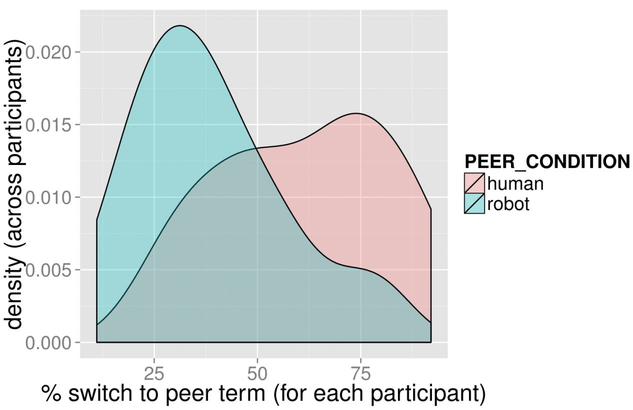

Figure 6: Cross-participant tendencies to switch to peer's term

4.4 Analysis 2: Switching terms, term likelihood, and personality traits

Next, we perform additional regression analyses, focusing only on the subset of the data where the participant had the opportunity to shift to the peer's term. In this analysis, the dependent variable is a TRUE vs. FALSE response, indicating whether or not the participant switched to a new term introduced by the peer.

In this model, as one predictor, we again have the PEER CONDITION (robot vs. human). Secondly, we have the PRIOR PROBABILITY of the word introduced by the peer. This measure represents how likely a particular word is as a response to a particular image, as indicated by a population of task participants. Specifically, to quantify the prior probability of a term, we calculate how often this particular response was offered by 58 participants in a pre-task. (This group consists of the 40 individuals in the current study, plus 18 from a separate pilot study). Thus, for instance, for an icon of a coffee cup, the prior probability of the word "cup" is .379, since this proportion of 58 respondents volunteered "cup". For the same image, the word "mug" has a prior probability of .121. We predict that prior probability of a term will give some indication of how appropriate, and how accessible, a particular label is for a given picture. Responses that, in the population as a whole, are more probable in the pre-task should be easier to prompt via peer influence as individuals' responses in the post-task.

As additional predictors, from the Big-Five personality traits [23], we investigated the influence of two traits in the task: Agreeableness, and Openness to experience. These two traits are chosen since there are theoretical motivations for a link between self-reported personality measures and tendencies to imitate other social agents. "Openness", as an element of the Big-Five, is said to encompass a range of linked personality traits, including curiosity and (most relevantly for the present experiment) an affinity for variety and novel experiences [23]. Previous research has shown that participants who are more "open" are more likely to imitate linguistic behaviours of their interlocutors [2]. "Agreeableness" on the other hand, describes how cooperative/compliant a person is, compared to quarrelsome/distrustful [20]. To acquire the Big-Five personality values we chose the TIPI test [15]. This test is a simple, fast and valid assessment system for the Big-Five which is not only used in the psychology community but also by other robotics researchers [30].

We performed logistic mixed-effects regression, including random intercepts for participants (random slope for PRIOR PROBABILITY) and items (random slope for PEER CONDITION and OPENNESS). The best-fitting model is summarised in Table 7. Agreeableness of the participant was not found to be significant, and it is thus excluded from the model. However, there were significant effects for PEER CONDITION, PRIOR PROBABILITY, and the participant's OPENNESS.

In this model, we first note that PEER CONDITION predicts switching; participants who have interacted with a human peer are more likely to switch terms than participants who interacted with a robot. Note that, in this model, peer condition is significant as a main effect (not just as an interaction), since in this dataset, we have restricted our focus to items where a peer-influenced switch could take place.

Secondly, we note that PRIOR PROBABILITY predicts participants' tendency to switch terms. Participants are more likely to adopt a word which has a high prior probability of use. However, note that in the model, this PRIOR PROBABILITY effect does not interact with PEER CONDITION. This suggests that the same kind of influence may be at work in the robot condition and the human condition; participants are more swayed by responses that are highly common (and thus presumably highly suitable) responses.

Finally, we note that the "openness" of the participant does not, as a main effect, predict the tendency to switch to the peer's term. However, this personality trait does interact with PRIOR PROBABILITY in a sensible way. This interaction can be visualised in the effect plot in Figure 7. This plot shows that participants who are less "open" to new experiences tend to carefully adhere to PRIOR PROBABILITY with respect to degree of influence; high-probability re-

	Estimate	Std.Error	z value	pval
(Intercept)	0.55	0.30	1.86	0.06
PEER_CONDITION = robot	-1.21	0.37	-3.315	< .001
PRIOR_PROBABILITY (item)	2.59	0.51	5.13	< .001
OPENNESS (participant)	0.25	0.18	1.36	0.18
PRIOR_PROB * OPENNESS	-0.94	0.42	-2.23	0.03

Table 7: Regression model summary: Tendency to switch to peer's term.

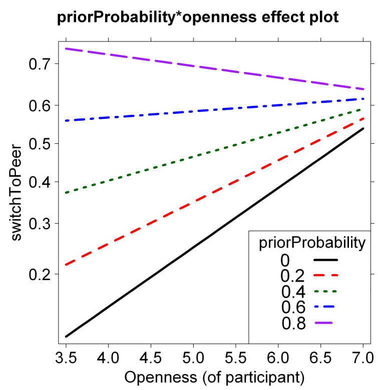

Figure 7: Interaction plot for subject personality*item predictability

sponses are likely to trigger a switch, but low-probability responses are unlikely. However, participants who score higher on OPENNESS are more likely to adopt all kinds of words introduced by their peer; such participants switch to low-probability terms in addition to high-probability ones. Interestingly, there is no interaction with PEER CONDITION; the personality trait seems to operate similarly whether the navigation peer was a human or a robot.

5. CONCLUSION & IMPLICATIONS

In this work, our aim is to see if a social robot can influence the word choice of a human interlocutor. We developed an experimental design in which the robot/actor and the human have to help each other proceed on a virtual game board. Moreover, to show to what extent the robot can influence the human, we created a pre-/main-/post-task experiment. By comparing the pre- and post-task we can study the influence of the robot. Furthermore, we are interested on how a social robot compares with a human actor.

Regarding the questions asked in the introduction section, whether social robots prompt lexical entrainment and whether it persists, the answer is yes. The current experiment proves that participants will shift their word choices to be more similar to those of robot interlocutors. This result supports previous lexical entrainment findings in a different context [17, 18], but extends such findings further. The current study measured effects separately from interactive tasks, and the entrainment is thus not merely for communicative ease. It is important to note that the timescale between the interaction with the robot and the measurement was about 30 minutes. Whether this short-term persistence also leads to long-term persistence is not yet tested by us. However, studies by Garrod et al.[13] support the notion that continued exposure and cooperation can lead to changes, and shared linguistic conventions, in a network of agents.

Looking at the influence of the robot compared to the actor, we can say that the lexical entrainment is similar under both conditions. However, as expected the robot's influence on humans was significantly weaker than the actor's (human-human). The reason why this could be is that robots might have a lower social status than humans. Furthermore, humans might include more subtle and unrecognised cues which were not repeated by the robot.

At this point, we should think about possible implications of persistent language change prompted by social robots. This is especially the case when we look at the sheer numbers of robots in development. We can consider, for instance, indicators from sales per unit, where service robots already overtook industrial robots. An overall purchase of 2.3 million units on industrial robots in the year 2011, compared to 2.5 million units of service robots is already a reality [38]. Second, the development can be observed in areas where robots are planned to be introduced, like classrooms, as help in offices, to work in sales, or as cleaners at home [6, 9, 21, 31]. If, in any case, social robots gain traction like service robots, and are used for all kinds of social interaction, they might have enough "power" to affect the language of a whole population. This effect is particular interesting to study when institutions, for example Apple or Google, provide the speech system for the robots. Any change such an institution makes on their speech system will most likely take immediate effect on all robots via updates. That means that whoever provides the future speech systems for robots, might hold the key for future language development in their hands.

6. RECOGNITIONS

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