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## **Predicting meaning in the dyad.**

Emilia Kerr<sup>1</sup>, Benjamin Morillon<sup>2</sup> & Kristof Strijkers<sup>1\*</sup>

<sup>1</sup> Aix-Marseille Université (AMU) & CNRS, Laboratoire de Parole et Langage (LPL), Aix-en-Provence,  
France.

<sup>2</sup> Aix-Marseille Université (AMU) & Inserm, Institut de Neurosciences des Systemes (INS), Marseille,  
France.

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OSF link to all materials and data: <https://osf.io/ujpb8/>

\* Corresponding author :

Kristof Strijkers

CNRS & Aix-Marseille Université (AMU)

LPL & ILCB

5 Avenue Pasteur

13001 Aix-en-Provence, France

Contact : [kristof.strijkers@univ-amu.fr](mailto:kristof.strijkers@univ-amu.fr)

## **Abstract**

This study investigated the role of meaning prediction in dyadic interactions. Participants engaged in a semantic association game where predictability of upcoming semantic categories was manipulated. Results showed that predictability sped up speech production in both interlocutors. Critically, our study reveals that meaning prediction not only aids language comprehension and subsequent speech production for the interlocutor completing a predictable sentence, but facilitates the verbal behavior from the conversational partner even more. This result demonstrates an incremental dyadic predictability effect in interlocutors during language interaction; a finding which offers empirical support for a key property of theories on joint action and interactive dialogue models, namely that successful social interaction and language use involve predicting and representing linguistic representations of ‘both’ partners in a dyad.

**Keywords:** Psycholinguistics, prediction, interaction, conversation, language production.

**Significance Statement:** “This study advances novel insights into how prediction not only aids individual comprehension and production, but can facilitate language processing incrementally between conversational partners in a dyadic setting.”

Prediction is generally believed to play an important role in language processing. Prediction can speed up our speech production and understanding, helps in avoiding errors, and ensures successful communication in conversation (e.g., Kutas et al., 2011; Pickering & Garrod, 2013; Huettig, 2015; Kuperberg & Jaeger, 2016; Pickering & Gambi, 2018). And even though it remains debated whether prediction is a necessary mechanism to process language (e.g., Huettig & Mani, 2016; Nieuwland et al., 2018), many behavioral and neuroimaging studies have shown that when prediction is possible it aids the processing of semantics, syntax, and phonology (e.g., Altmann & Kamide, 1999; Federmeier & Kutas, 1999; DeLong et al., 2005; Van Berkum et al., 2005; Staub & Clifton, 2006; Grisoni et al., 2017; Ito et al., 2018; Strijkers et al., 2019; Giroud et al., 2023). Most of this work has focussed on the effect of prediction within the individual, where for instance the speed of processing for a final word is compared between a highly constraining versus unconstrained context. Much less investigations have been done exploring the role of prediction in the dyad (e.g., Corps et al., 2018). This is important though, not only because it concerns our most frequent form of language use (e.g., Clark, 1996), but also to investigate whether prediction affects communication across interlocutors, as hypothesized by interactive language models of dialogue (e.g. Pickering & Garrod, 2021). While we have plenty of evidence demonstrating that predictable contexts can facilitate the comprehension or production of upcoming language within an interlocutor, we currently lack evidence demonstrating that such predictions also facilitate the linguistic behavior of our conversational partner. With the current study we aim at addressing this open issue by introducing a novel paradigm where two interlocutors play word association games in either predictive or unpredictable contexts.

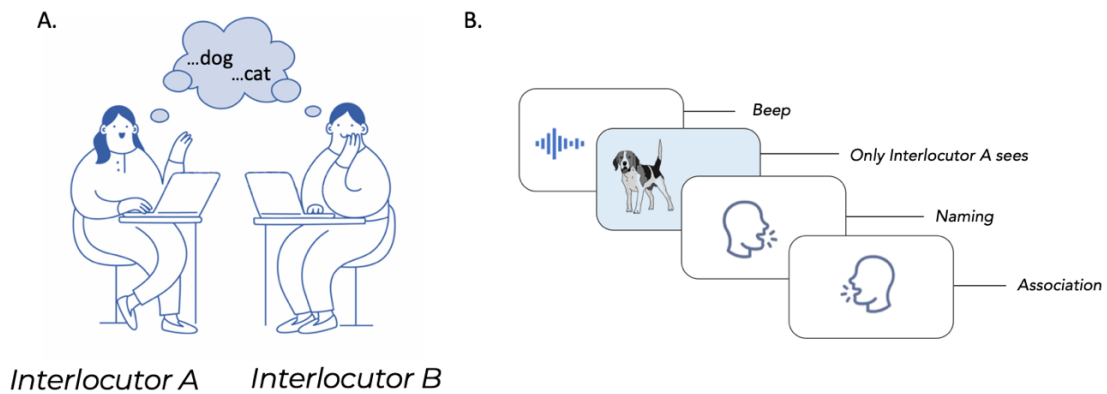
Psycholinguistic research within the dyad is not new, but remains scarce and is mainly focussed on alignment, where interlocutors tend to copy each other's linguistic behavior (e.g., Garrod & Anderson, 1987; Brennan & Clark, 1996; Branigan et al., 2000; Hartsuiker et al., 2004), or joint action, where speakers need to coordinate their language use to achieve a common goal (e.g., Brennan et al., 2010; Kuhlen & Abdel Rahman, 2023). Prediction in interaction has also been investigated, but mainly

in how it affects turn-taking in listeners (e.g., Levinson, 2016). Participants are faster responding to questions, either with button-presses (e.g., De Ruiter et al., 2006; Magyari et al., 2014; Ryskin et al., 2020) or verbal responses (e.g., Bogels et al., 2015; Corps et al., 2018; see also for written responses: Corps & Pickering, 2023), when the content of those questions is predictable. For instance, Corps and colleagues (2018) observed that people are faster in giving simple yes/no replies to questions when sentence meaning is predictable (e.g., *Are dogs your favorite animal?*) compared to when the content of the question is not predictable (e.g., *Do you enjoy going to the supermarket?*). These findings are compatible with studies demonstrating that prediction aids language comprehension (e.g., Altmann & Kamide, 1999; Staub & Clifton, 2006; Ito et al., 2018), and show that listeners can use those predictions to speed up their own speech planning.

In the present study we want to take these findings one step further and test whether meaning predictions affect dyadic interactions. That is, we will investigate the impact of prediction in two participants (rather than one) engaging in interaction with each other and explore whether meaning predictability not only speeds up the naming behaviour of an interlocutor completing a sentence, but also the replies given by the conversational partner.

To do so, we developed a paradigm where two participants play simple word association games with each other (see Figure 1). One interlocutor names an object presented on a computer screen (e.g., *dog*), and the conversational partner can freely reply, as long as the reply concerns a word from the same semantic category (e.g., *cat*). The paradigm thus concerns a simplified “mimicking” of conversational acts in that interlocutors can reply what they want as long as it is meaning relevant, but retains elements of a controlled design in that the experimenter dictates the input of the word association game. To manipulate predictability, the input (e.g., picture of a ‘*dog*’) could be preceded by an unpredictable sentence context (e.g., *‘Outside my window I saw a...’*) or a predictable sentence context (e.g., *‘Man’s best friend is a...’*). Just as found in the work on turn-taking (e.g., Bogels et al., 2015; Corps et al., 2018), completing a predictable sentence should go faster than an unpredictable sentence. The key question here is whether it

will also facilitate the naming behaviour of the conversational partner who formulates a reply. If dialogue models rooted in prediction are correct (e.g., Pickering & Garrod, 2013; Pickering & Gambi, 2018), the hypothesis is that prediction should facilitate language production of both interlocutors to a similar extent.



**Figure 1.** A visual representation of the experimental setting and design. A. Participants are seated across each other, and both have presentation laptops in front of them. B. In all three conditions participants first hear an auditory input, a beep sound, or a sentence, preceded by an image appearing on the Interlocutor A's screen. Interlocutor A names the image, and Interlocutor B replies with an association that belongs to the same semantic category, i.e., either an animal or a tool.

## Methods

All materials, the code, analyses pipelines and raw data are made freely available on our online OSF repository (<https://osf.io/ujob8/>).

### Participants

40 French native speakers (34 female) were recruited to form 20 dyads. All participants were between 18 and 40 years old (mean age = 21.02 (SD = 2.18), had no neurological or speech disorders and had normal or corrected to normal vision. Each was paid 10 euro per session and received course credit if required.

### Materials

36 French words were chosen, half of which corresponded to animal names and half to tool names, and which serve as picture input to start a dyadic interaction (items selected from the MultiPic database: Duñabeitia et al., 2018). We choose those two categories because they are well-established semantic categories with non-overlapping meaning representations (e.g., Caramazza & Mahon, 2003), are easily depictable, and categories with many lexical items allowing for a wide range of possible replies. We controlled the stimuli for their lexical frequency (animal words:  $M=5.65$ ,  $SD=8.19$ ; tool words:  $M=9.68$ ,  $SD=12.9$ ), number of letters (animal words:  $M=6.94$ ,  $SD=1.80$ ; tool words:  $M=6.61$ ,  $SD=1.24$ ) and number of syllables (animal words:  $M=2.22$ ,  $SD=0.88$ ; tool words:  $M=1.89$ ,  $SD=0.58$ ). We then constructed for each of the stimuli highly predictable (HP) and unpredictable (UN) sentences (see Table 1). To make sure that the sentences fulfilled the predictability requirement, a cloze-probability test (Bloom & Fischler, 1980; Block and Baldwin, 2010) was conducted online with 68 respondents (using the online FindingFive platform following criteria from previous work: Fairs & Strijkers, 2021). In this test participants were asked to complete the sentences with a word that first comes to their mind. We only kept those sentences for which at least 70% of the respondents gave the intended item. The mean cloze-probability result for the animal category was 86.4% ( $SD=8.7$ ), and the mean cloze-probability result for the tool category was 87% ( $SD=8.9$ ). Among the sentences in the UN condition, the highest probability score was 38%. Relying on this cut-off, we were left with 18 items and corresponding HP sentences in the animal category and 18 items and corresponding HP sentences in the tool lists (full stimuli set: <https://osf.io/ujpb8/>). Per item, the length (number of words) of the HP and UN sentences was identical.

| <i>Category</i> | <i>Word</i>             | <i>Highly predictable sentence</i>                                                               | <i>Non-predictable sentence</i>                                                          |
|-----------------|-------------------------|--------------------------------------------------------------------------------------------------|------------------------------------------------------------------------------------------|
| animal          | <b>âne</b><br>(donkey)  | Bourriquet, l'ami de winnie-l'ourson, était un...<br>(Eyore, Winnie-the-Pooh's friend, is a...). | Au marché hier, il a pensé à acheter un...<br>(At the market yesterday, he bought a...). |
| tool            | <b>balai</b><br>(broom) | Elle nettoie le sol avec un...<br>(She is sweeping the floor with a...).                         | Je ne trouve toujours pas un...<br>(I still can't find a...).                            |

**Table 1.** Examples of the stimuli

### ***Task and procedure***

The experiment setup is shown in Figure 1. A trial had the following sequence: Interlocutor A saw an image and named the object aloud (i.e., standard object naming; e.g., Levelt, 1989), while Interlocutor B responded to the utterance of Interlocutor A with a semantically related word. They alternated roles in each trial. In the baseline condition (the Isolated Word condition; IW), participants heard a beep as attentional cue to signal the start of a trial. To explore the effect of predictability, two additional conditions were included: the highly predictable (HP) and unpredictable (UN) conditions. In these, both participants in the dyad heard auditorily presented sentences from the cloze-probability test (instead of the beep in the IW), after which an object was presented and Interlocutor A had to complete the sentence by naming the object (for similar sentence completion designs see e.g., Griffin & Bock, 1998; Ferreira & Griffin, 2003; Drake & Corley, 2015; Kleinman et al., 2015). Just as in the IW condition, Interlocutor B had to respond to Interlocutor A with a categorically related word. All participants cycled through all three conditions, which were administered randomly, for a total of 216 trials (72 per condition), with each stimulus repeated six times.

### **Analyses**

Analyses included Linear Mixed Effects Model (LME) to analyze reaction times (naming latencies) with ‘condition’ (IW, HP and UN), ‘repetition’ (from 1 to 6) and ‘category’ (‘animal’ or ‘tool’) as fixed effects and ‘dyads’ and ‘items’ as crossed random effects (Baayen et al., 2008; Barr et al., 2013). The models were fitted with `lmer` (for LME) function from the `lme4` package (Bates et al., 2015) in the R statistical computing environment (version 4.2.0, R Core Team, 2022) and the `Pymer4` library in Python (Jolly, 2018). We used the control condition as the reference. Reaction times were log-transformed prior to analysis. We used the maximal random structure model that converged (Barr et al., 2013), and this included by-dyad and by-item random intercepts.



## Results

To compute the main results, we included correct trials only. From the total 4320 trials 436 were removed due to either a wrong response or no response by either interlocutor, or when a word was preceded by an article, verbalised hesitation, or self-correction. Hence, 3884 correct trials (89.9%) entered the analyses. Using a combination of Python and Praat scripts (<https://osf.io/ujpb8/>), we calculated speech onset times for Interlocutor A as the picture onset to their speech onset, and for the Interlocutor B from Interlocutor A's speech offset to Interlocutor B's speech onset. Note, importantly, that by calculating Interlocutor B's naming latencies after Interlocutor A's response (rather than from stimulus onset or Interlocutor A's speech onset), the naming latencies of Interlocutor B are independent from the speed of naming of Interlocutor A. The mean reaction times are presented in Tables 2 and 3, and the response distributions per condition in Figure 2.

Below we report regression coefficients ( $b$ ), standard errors (SE),  $t$ -values, corresponding  $p$ -values and Cohen's  $d$ . For Interlocutor A, reaction times were significantly faster in the Predictable (HP) and Unpredictable (UN) conditions compared to the Isolated Word (IW) condition (HP condition:  $b = 0.39$ ,  $SE = 0.058$ ,  $t = 6.70$ ,  $p < 0.001$ ,  $d = 0.67$ ; UN condition:  $b = 0.121$ ,  $SE = 0.043$ ,  $t = 2.85$ ,  $p = 0.007$ ,  $d = 0.22$ ). A direct comparison between the HP and UN likewise resulted in significant differences, with faster responses in the HP condition ( $b = 0.264$ ,  $SE = 0.053$ ,  $t = 4.950$ ,  $p = < 0.001$ ,  $d = 0.47$ ). Additionally, while Interlocutor A was progressively faster with each repetition of an item ( $b$

| Condition     | N    | Interlocutor A RT | SD     | SE    | CI    |
|---------------|------|-------------------|--------|-------|-------|
| Isolated Word | 1282 | 1092              | 568.63 | 15.88 | 31.15 |
| Predictable   | 1321 | 740               | 481.93 | 13.25 | 26.01 |
| Unpredictable | 1281 | 974               | 508.36 | 14.20 | 27.86 |

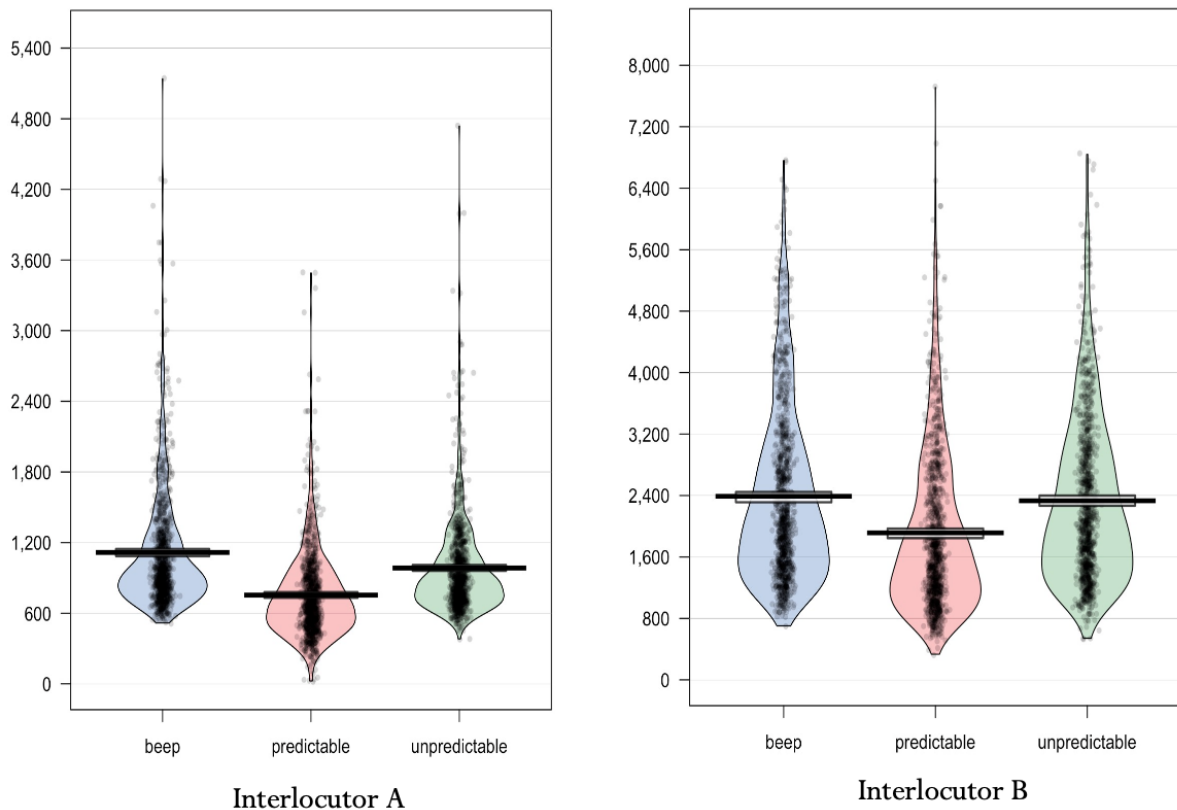
**Table 2.** Mean reaction times (msec) per condition for Interlocutor A.

| Condition     | N    | Interlocutor B RT | SD      | SE    | CI    |
|---------------|------|-------------------|---------|-------|-------|
| Isolated Word | 1282 | 2309              | 1233.15 | 34.44 | 67.56 |
| Predictable   | 1321 | 1875              | 1189.93 | 32.73 | 64.22 |
| Unpredictable | 1281 | 2276              | 1216.73 | 33.99 | 66.69 |

**Table 3.** Mean reaction times (msec) per condition for Interlocutor B.

= 0.053, SE = 0.009,  $t = 5.865$ ,  $p < 0.001$ ), importantly, there was no significant interaction between the HP and Repetition or between the UN and Repetition ( $p = 0.218$  and  $p = 0.745$ , respectively). Also, category did not affect the response times of the Interlocutor A ( $p = 0.447$ ).

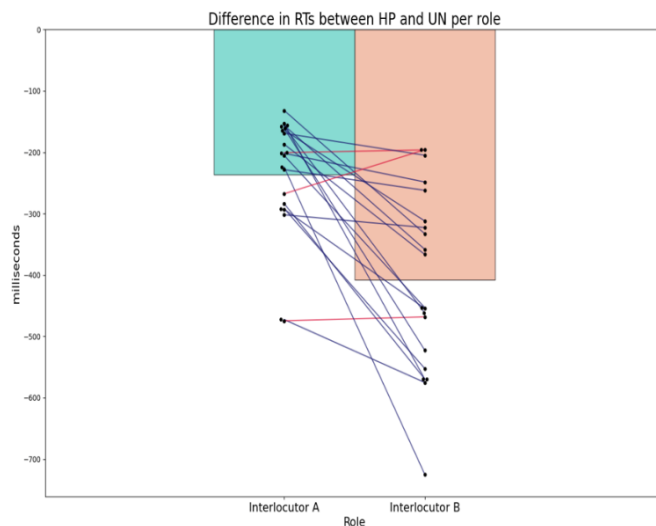
Importantly, also for Interlocutor B reaction times were significantly faster in the HP condition compared to IW ( $b = 0.219$ , SE = 0.05,  $t = 4.39$ ,  $p < 0.001$ ,  $d = 0.36$ ) and compared to the UN ( $b = 0.240$ , SE = 0.06,  $t = 4.356$ ,  $p < 0.001$ ,  $d = 0.35$ ). There was no significant difference between IW and UN ( $p = 0.607$ ). Interlocutor B's reaction times did not progressively differ with each Repetition ( $p = 0.112$ ), and the interaction between Repetition and Predictability was not significant ( $p = 0.551$  for the HP, and  $p = 0.375$  for the UN). Also, Interlocutor B was faster replying to stimuli denoting animals compared to tools ( $b = 0.082$ , SE = 0.033,  $t = 2.505$ ,  $p = 0.02$ ), suggesting that it was easier to find animal than tool associates.



**Figure 2.** Pirate plots visualising the reaction time distributions for Interlocutor A (left) and Interlocutor B (right) per condition (blue – IW, red – HP, green – UN). Grey dots reflect each datapoint per condition and black lines index the average reaction times (in msec) per condition.

We also compared the roles of Interlocutor A and B directly by including ‘Role’ as a fixed effect in the model. We observed a significant effect of Role ( $b = 0.703$ ,  $SE = 0.05$ ,  $t = 14.33$ ,  $p < 0.001$ ,  $d = 1.30$ ), with overall faster reaction times for interlocutor A than interlocutor B (see Tables 2 and 3). Interestingly, the interaction between Role and Predictability (HP – UN) was significant ( $b = 0.203$ ,  $SE = 0.046$ ,  $t = 4.439$ ,  $p < 0.001$ ,  $d = 1.05$ ). This result highlights stronger prediction effects for interlocutor B than interlocutor A in a given dyad (see Figure 3).

Finally, we also explored psycholinguistic variables of the responses given by the Interlocutor B known to affect response time speed (e.g., Strijkers et al., 2010), to assess whether these variables would differ between the predictability conditions. The lexical frequency of the responses given by Interlocutor B did not differ in the HP condition ( $p = 0.952$ ) or the UN condition ( $p = 0.377$ ) compared to the control condition. The lexical frequency also did not differ with repetition ( $p = 0.9$ ), or between tool and animal categories ( $p = 0.537$ ). Likewise, the replies given by Interlocutor B did not differ in word length (phonemes or syllables) for the HP condition ( $p = 0.227$ ), the UN condition ( $p = 0.888$ ), repetition of a



**Figure 3.** Representation of the prediction effect (expressed in ‘reaction time gain’ by subtracting HP from UN) per role in each dyad. Black dots represent individual dyads, with blue lines connecting those interlocutors of the same dyad where the prediction effect (gain) was bigger for Interlocutor B and with red lines connecting those interlocutors of the same dyad where the prediction effect (gain) was bigger for Interlocutor A. The turquoise bar shows the average gain for Interlocutor A and the orange bar shows the average gain for Interlocutor B.

stimulus ( $p = 0.136$ ), or category ( $p = 0.932$ ) compared to the control condition. Of the replies given by Interlocutor B, broken down by the number of repetitions, 50.3% of responses were unique, 19.9% were repeated once, 10.8% were repeated twice, 8.2% were repeated three times, 5% were repeated four times, and 1.8% were repeated more than four times. In sum, neither differences in psycholinguistic properties like frequency or length of given

replies nor excessive repetition of the same reply can account for the huge prediction effects observed in the experiment.

## **Discussion**

In the present study we investigated whether meaning prediction occurs in a dyadic interaction, and whether it facilitates the communicative behaviour of both interlocutors. In the experiment dyads of participants engaged in a simple semantic association game where we manipulated whether the upcoming semantic category could be predicted or not. Results demonstrated that when the meaning of the upcoming utterance can be predicted, speech production is speed up by at least 200 ms in both interlocutors, and in an incremental fashion. Faster naming latencies for the interlocutor who completes the predictable sentence (*interlocutor A*) replicates previous research that shows that meaning prediction aids language comprehension (e.g., Altmann & Kamide, 1999; Staub & Clifton, 2006; Ito et al., 2016; Grisoni et al., 2017), which in turn facilitates that listener's own productions to complete a sentence (e.g., Griffin & Bock, 1998; Drake & Corley, 2015; Kleinman et al., 2015; Staub et al., 2015), or to formulate an answer to the perceived sentence (e.g., Bogels et al., 2015; Corps et al., 2018). The important contribution here is that meaning prediction also facilitates the replies given by the conversational partner (*interlocutor B*), and this dyadic predictability effect is even 'larger' compared to the sentence completion response to which the original prediction applied (Figure 3).

This finding is in line with work on joint action which proposes that successful social interaction requires predicting and representing perceptual, motor and cognitive representations of our partner (e.g., Sebanz et al., 2006; Sebanz & Knoblich, 2009). Similarly, for language, intrinsically a social act (e.g., Tanenhaus & Brown-Schmidt, 2008), evidence has cumulated showing that we do not only activate language representations we intend to utter ourselves, but also those of our conversational partner in order to predict that partner's verbal behaviour (e.g., Brennan et al., 2010; Baus et al., 2014; Gambi et al., 2015; Kuhlen & Abdel Rahman, 2017; 2023; Brehm et al., 2019; Cirillo et al., 2022). Our results

extend this work by highlighting that thanks to predicting from which semantic category our partner will utter a lexical item, we ourselves can prepare in advance a meaningful reply, which speeds up our proper productions and substantially facilitates the conversational interaction. This dynamic of simulating the linguistic representations of other interlocutors via predictive processing in order to enhance communication and alignment between language users is exactly the mechanism proposed by interactive dialogue models rooted in prediction (e.g., Pickering & Garrod, 2013; Pickering & Gambi, 2018). The present study offers empirical evidence for this role of prediction in the dyad and confirms a key property of interactive dialogue models, namely that predictive processing not only facilitates language processing of the interlocutor to whom the predictive content applies, but also that of the partner who participates in the conversation; in fact, if anything, the impact of prediction is stronger for the latter, which is highly suggestive that predictive processing could indeed be the key mechanism for alignment.

In conclusion, relying on a novel dyadic paradigm combining controlled picture naming with more free associative naming, we demonstrated that prediction strongly facilitates the verbal behavior of both interlocutors engaging in conversation. Such synergetic dyadic predictions can aid communication and alignment as suggested by interactive dialogue models.

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### **Author contributions**

E.K. and K.S. conceptualized the study. E.K, B.M. and K.S. designed and implemented the study. E.K. collected the data. E.K., B.M and K.S. analyzed the data. E.K. and K.S. wrote the initial draft. All authors reviewed the manuscript.