Influence of social and semantic contexts in processing speech in noise

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ABSTRACT

Social interactions occupy a substantial part in our life, and listening to others' interactions is crucial for understanding our social world. While the role of semantics in speech comprehension is well-known, the role of social context and its interaction with semantics is less explored. Audiological tests of hearing in noise often use sentences but do not reflect typical speech, which occurs in conversations. We conducted four perceptual experiments to understand third-person processing of multiple-speaker conversations, manipulating social and semantic contexts. We used AI-generated auditory stimuli of two-speaker dialogues or one-speaker monologues (social context) arranged in intact or scrambled order (semantic context). Each trial had five sentences, with the fifth embedded in multi-talker babble noise. The fifth sentence was then repeated without noise, with one word either altered or unchanged. Healthy young adults identified whether the repeated sentence was the same or different from the in-noise sentence. Across experiments (total N=195), both social and semantic contexts influenced speech-in-noise processing. Furthermore, individual performances correlated with social traits, suggesting those with higher social functioning utilized conversational cues better. These findings highlight that both semantic and social aspects modulate conversation processing, raising questions about predictive and other mechanisms for speech perception in social contexts.

KEYWORDS

Speech-in-noise, Conversations, Context, Social, Semantic

I. INTRODUCTION

During our lifetime, we humans have to manifest complex abilities to navigate our social world (Adolphs, 2001, 2009). Consequently, a significant portion of our existence is devoted to engaging in social interactions with others. Not only do we interact in the first person, but listening to others' interactions also serves critical functions in understanding our social world. Indeed, information about our social world comes first through our senses, and humans rely heavily on audition to communicate with their conspecifics (Adolphs, 2001). Thus, impairments in auditory functions can have detrimental effects on quality of life for a person by degrading their social interactions and provoking isolation from others (Ciorba et al., 2012; Dalton et al., 2003; Nordvik et al., 2018). Therefore, a deeper understanding of the factors having an influence on perceiving social signals through audition is crucial both for the basic science of auditory cognition and for understanding the consequences of hearing loss.

A recurring complaint among those with hearing loss is the experience of sometimes being able to hear a conversation yet struggling to comprehend the spoken words, especially in acoustically challenging environments (Wilson, 2003). The importance of evaluating recognition performance of speech presented in background noise as an ecological measure of hearing loss was highlighted over 50 years ago (Carhart & Tillman, 1970). Despite this early recognition, it is only in the last decades that such evaluations have been integrated as a standard component of audiological test batteries (Strom, 2006). The conventional approach to assessing hearing loss – based primarily on pure-tone thresholds – has been found to offer limited predictive value for speech intelligibility in noise (Nilsson et al., 1994), prompting the development of novel assessments that specifically measure the ability to discern speech sounds from background noise across different signal-to-noise ratios (SNRs). Emerging from these efforts are tests such as the

Hearing-in-Noise Task (HINT; Nilsson et al., 1994), the Speech-in-Noise Task (QuickSIN; Killion et al., 2004), and the Word-in-Noise Task (WIN; Wilson, 2003). While these assessments have significantly contributed to understanding hearing abilities in controlled environments, their applicability to real-life social situations, such as listening to a conversation between two or more speakers, remains limited. Indeed, these tests are all based exclusively on the recognition of words or sentences presented in isolation, while in the context of a real-life conversation speech is never heard in an artificially isolated manner.

Traditionally, the assessment of word or sentence recognition in noise has heavily relied on bottom-up cues (Parthasarathy et al., 2020), manipulated through varying SNRs. However, recent research suggests that speech perception relies on additional, top-down processes. Indeed, contextual factors such as semantic cues have been shown to exert a substantial influence on speech perception, especially in challenging auditory environments. For instance, adding congruent or incongruent cues before a sentence (Zekveld et al., 2011, 2012, 2013), using word priming (Golestani et al., 2009, 2013), tweaking word probabilities (Roland et al., 2012) or using nonsense sentences (O'Neill et al., 2021) are some manipulations that showed a significance influence on speech perception. As for the mechanisms involved, it has been proposed that high-level semantic information would propagate down through hierarchical levels, first activating representations associated with the phonetic features of the speech and then with the lower-level acoustic features (Broderick et al., 2019; Sohoglu et al., 2012). In this framework, higher-level inferences would preactivate lower-level representations before the arrival of bottom-up auditory information (Kuperberg & Jaeger, 2016), that would facilitate the processing of bottom-up input. Alternatively, it has been proposed that cognitive resources may be dynamically allocated between the semantic and auditory systems to deal with the perceptual and cognitive loads of incoming

words (Mattys et al., 2009; Strauß et al., 2013). In this framework, words that are more dissimilar to their previous context would bear more information and thus would lead to a higher processing load on the semantic system (Broderick et al., 2019). As a result, a loaded semantic system would lead to reduced tracking of words in the auditory system. Critically, beyond these mechanisms it is important to note that, although we know speech patterns at different timescale are processed using different mechanisms and/or brain regions (DeWitt & Rauschecker, 2012; Farbood et al., 2015), only a few studies examined the effects of semantics in the context of an entire conversation. Indeed, although some studies have examined the influence of large-scale contexts on speech perception, using tools such as the Connected Speech Test (Cox et al., 1987) or naturalistic dialogues from the LUCID corpus (Baker & Hazan, 2010, 2011), most of these studies mainly focused on immediate topic transitions or isolated word or sentence contexts, whereas our study uniquely manipulates semantic cues as part of a broader conversation-level context.

Going further, the influence of context in perception of a stimulus is not only known in the auditory modality but also in the visual modality (Brandman & Peelen, 2017; Oliva & Torralba, 2007), where recent work showed that a social context can have a significant influence on the perception of an individual visual stimulus and its neural processing (Abassi et al., 2020; Bellot et al., 2021). Although the hierarchy of information processing shows analogies in the visual and auditory modalities (Iamshchinina et al., 2022), a significant gap exists in the literature on audition regarding the understanding of the impact of a social context on perceiving verbal sentences, especially in conditions where the auditory environment is challenging. The social context encompasses not only semantic cues but also involves intricate mechanisms related to the interplay between two or more speakers, elements that are generally overlooked in the examination of higher-order top-down cues, and that is a second gap we aimed to fill in the current study.

Overall, through a set of four experiments, the present study aims to investigate the influence of both semantic and social contexts in the third-person understanding of a conversation between two speakers in challenging listening conditions. To do so, we manipulated the global content of a conversation to create different contexts for a listener along these two factors. To manipulate the semantic context, in one condition we altered the order of the sentences constituting of a prototypical conversation while keeping the content of the individual sentences unaltered (sentence-scrambled condition), and a control condition we kept the order of the sentences intact (intact condition). To manipulate the social context, in one condition we used one-speaker monologues (non-social condition) and in another condition we used two-speakers dialogues (social condition), while keeping the semantic content identical. Unlike monologues, dialogues involve turn-taking and interactive dynamics, which we hypothesize would create a richer social context that could enhance speech processing in degraded listening conditions. The last sentences of each of these conversations were then embedded in multi-talker babble noise and used in a discrimination task with healthy young adults. The first experiment was designed to identify the appropriate signal-to-noise ratio (SNR) to be used in subsequent experiments. Here, we expected a correct SNR to not produce ceiling or floor effects when performing our task while limiting subject frustration. The second experiment was designed to specifically address the influence of semantic context (i.e., intact vs. sentence-scrambled conversations) while controlling for the effect of social context (i.e., separate blocks of dialogues and monologues). Here, if there is an effect of semantic context at the broad conversation level, we expected better processing of the intact conversations as compared to the sentence-scrambled ones. A third experiment specifically addresses the influence of social context by manipulating the number of speakers in a conversation (i.e., monologues vs. dialogues) while controlling for the effect of semantic context (i.e., separate

blocks of intact and scrambled conversations). Here, if there is an effect of social context at the broad conversation level, we expected better processing of the dialogues as compared to the monologues. The fourth experiment was designed to address the interplay between the effects of semantic and social contexts by manipulating both the social and semantic contexts of a conversation at the same time. Here, if there is an interplay between these two factors, we expected to find an interaction between them. Finally, we also tested whether individual differences in processing conversations can be linked to individual social traits. Indeed, previous research showed that performances in processing of social stimuli could be linked to social traits for both the auditory (Gervais et al., 2004; Schelinski et al., 2016; Skuk et al., 2019; Stewart & Ota, 2008) and visual (Abassi & Papeo, 2022; van Boxtel et al., 2017; Wyer et al., 2012; Yang et al., 2024) modalities, suggesting that these perceptual measures could be used as potential indicators of social abilities. We thus asked whether our task could similarly be used as one of those indicators.For this purpose we used the Autism Quotient (AQ; Baron-Cohen et al., 2001) as a measure of social abilities. We expected to find a significant relationship between individual performances in processing a conversation and this individual measure of social traits.

II. METHODS

A. Participants. A total of 295 participants (for which details are given below) took part in the experiments online and were recruited on the prolific platform (*www.prolific.com*). Overall, the minimal sample size for each experiment was based on previous literature using analogous word-recognition tasks in multitalker babble noise. More specifically, Killion et al. (2004) found significant results for the QuickSIN test using 16 participants while Wilson (2003) used 24 participants for the WIN test. In the current study, excepted for experiment 1 that was used to pilot SNR for following experiments, we used a minimum of 59 participants (after exclusions) for all

experiment, which should be a sufficient sample size to assess our effects of interest based on previous literature. All participants read and signed an informed consent form prior to participating in the study and were remunerated 6£ for 40 minutes of their time. They were all American English first language speakers with normal hearing (confirmed by self-reported online), aged between 18 and 35 years.

B. Stimuli. The entire set of stimuli can be found online at www.zlab.mcgill.ca/stimuli/ ("Stimuli_from_Abassi_2024"). The main stimuli set consisted of English two-speaker dialogues or one-speaker monologues (factor: social context) arranged in intact or sentence-scrambled order (factor: semantic context) (Fig. 1). All stimuli were created using a combination of ChatGPT (GPT-3.5, *OpenAI*) to generate the contents of the conversations and Google text-to-speech AI to convert the textual conversations into natural-sounding speech. Each conversation was carefully constructed to ensure that dialogues and monologues had the same sentence structures and themes, isolating the effect of social context. Indeed, dialogues featured alternating speakers, providing turn-taking cues and interactive dynamics that were absent in monologues. This design allowed us to investigate how the presence of two interacting voices, versus a single continuous voice, influences the listener's processing of speech. More specifically, we first used ChatGPT to generate the text of 35 five-sentence conversations based on five themes (Music, Cinema, Sport, Literature and Travel). An example of the ChatGPT prompts used is *"On the topic of music, write X conversations of five sentences each between two persons with a maximum of fifteen words per sentences"*. We did not use the exact conversation contents as generated by ChatGPT, but we made modifications such as word, syntax, and length changes to enhance the naturalistic aspect of each item. For each five-sentence conversation, we created a sixth sentence, that was same as the fifth sentence, but with only one word change that could appear at the beginning, the middle or the end

of the sentences. The word change itself was unrelated to the content of the conversation—that is, it was a neutral word within the sentence that would be equally appropriate in the context (see Fig 1) and, when applicable, had similar number of syllables. Thus, the manipulations were exclusively related to the *context* within which the target sentence was presented, and not to the structure or content of the target sentence itself We note that only the 5th sentence was presented in noise (see below).

Prior to converting the conversations to natural-sounding speech, we added prosody tags in each sentence to make it sound more naturalistic, following the Speech Synthesis Markup Language (SSML) rules. An example of an edited sentence with prosody tags is *"*I *<prosody rate="fast" pitch="+4st">* love *</prosody>* playing *<prosody pitch="-2st">* music *</prosody>"*. The complete list of sentences with their prosody tags is available in the stimuli dataset package. We then selected two voices from the list proposed by Google text-to-speech AI: one female voice (*'en-US-Wavenet-G'*) and one male voice (*'en-US-Wavenet-J'*). We finally converted each text sentence of each conversation into auditory speech for the two voices, and we normalized all audio tracks to have the same root mean squared (RMS) amplitude across all sentences.

We then arranged the sentences into conversations as follows. For intact dialogues, half of the conversations began with the female voice and alternated with the male voice, and for the other half it was the opposite. For monologues, half of the conversations were composed of the female voice only, while the other half was composed of the male voice only. Furthermore, for both dialogues and monologues, sentence-scrambled conversations were created by randomly shifting sentences across the conversations, except for the first and fifth sentences. In total, we created 240 conversational stimuli (70 stimuli by unique condition, half primed with female voice and half

primed with male voice). Between two sentences, we added a silent gap randomized between 400 and 600 ms, except between the fifth and the sixth sentences, where a silent gap of 1 s. was added. In average, each full conversation stimuli had a total duration of ~18 s.

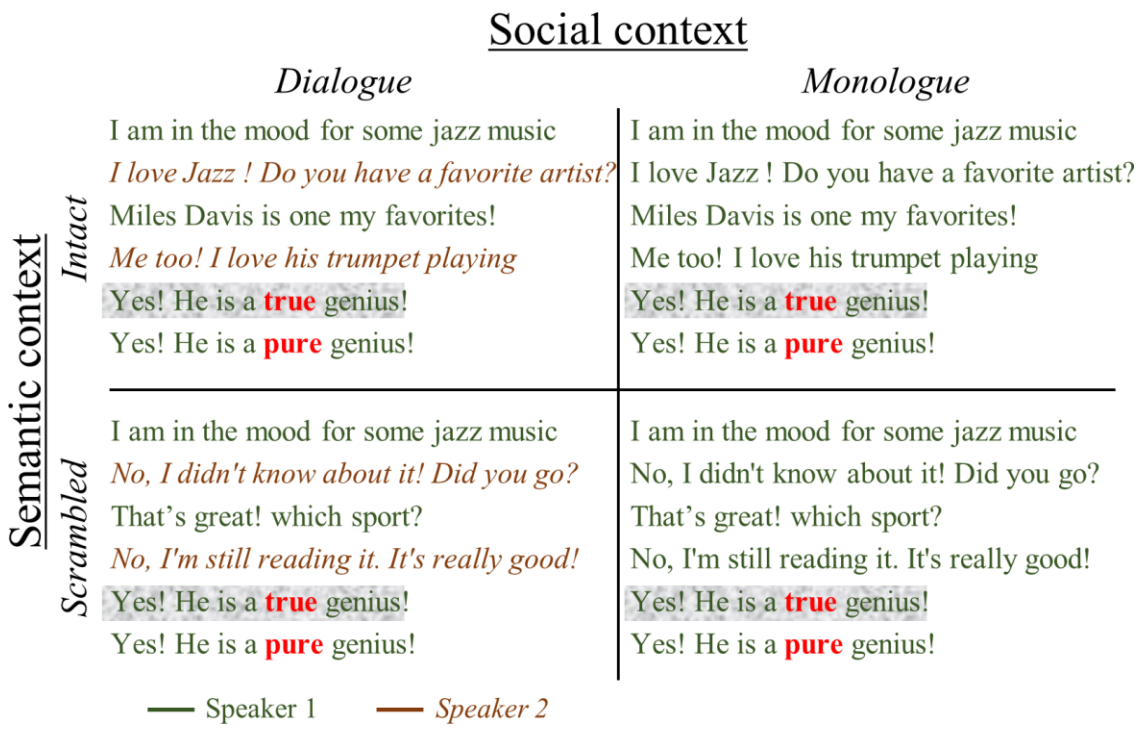


Figure 1. Example of conversations composing the stimuli set. Stimuli are arranged following a 2x2 design with factors social context (Dialogue / Monologue) and semantic context (Intact / Scrambled). For dialogues, sentences presented in normal green alternating with brown italic represents the alternance between the two speakers (one female and one male. Sentences presented over grey background illustrate that the fifth sentence of each conversation was always embedded in noise. The last sentence could be either the same or different than the previous one, with only one word changing for the different sentences, as represented in bold red.

In addition to dialogues and monologues, we created a baseline set of 50 one-sentence stimuli that were different than the sentences used in the conversations, that were used as a baseline condition. For each of these sentences, we created another sentence, that was same as the original sentence, but with only one word change that could appear at the beginning, the middle or the end

of the sentences. The word change itself was unrelated to the content of the conversation—that is, it was a neutral word within the sentence that would be equally appropriate in the context. We then converted these sentences into natural-sounding speech for both female and male voices, using the same method than for conversations. More specifically, one example of the ChatGPT prompts used to generate the text of these one-sentence stimuli was *"Write X sentences on the topic of music with a maximum of fifteen words per sentences".* We then added prosody tags following SSML rules and transformed it into audio using Google text-to-speech. In total, we created 100 one-sentence stimuli (50 for female and 50 for male), for an average duration of ~5 s. each.

C. Multi-talker babble noise. In a second step, we embedded the fifth sentence of each conversation and the one-sentence baseline stimuli into multi-talker babble noise. We used multi-talker babble noise as a masker for our stimuli because we wanted it to be as naturalistic as possible (for a review on the different type of maskers, see Assmann & Summerfield, 2006). The rationale to create this noise was as follow: 1) We used a total of 8 competing voices (4 females and 4 males), that is a good compromise between creating sufficient interference with the target voices while keeping a reasonable amount of competing voices (Cooke, 2006; Li & Lutman, 2006; Miller, 1947; Simpson & Cooke, 2005); 2) We selected the fundamental frequencies (f0) of the competing voices so it would not overlap with the target voices, as having too close f0 between target and competing voices may interfere with the task (Assmann, 1999; Bird, 1997; Brokx & Nooteboom, 1982; David et al., 2017; Lee & Humes, 2012); 3) We selected a f0 range between ~121 Hz and ~201 Hz by steps of around one semi-tone between each voice (see supplementary Figure 1), so the range would be large enough to cover a representative range of f0 in the general population (see Cristina Oliveira et al., 2021).

To generate the content of the noise sentences, we again used ChatGPT to generate 24 semantically anomalous sentences in English. Anomalous sentences were used here to eliminate the possibility that participants might extract an entire meaningful sentence from a speaker other than the target while keeping a correct grammar (Van Engen & Bradlow, 2007). An example of the ChatGPT prompts used is *"Write X anomalous sentences"* and an example of the anomalous sentences generated is *"Her purple umbrella whistled a dolphin"*. We then selected eight voices from the list proposed by Google text-to-speech AI: 4 females voices (*'en-US-News-K'; 'en-US-News-L'; 'en-US-Wavenet-E'; 'en-US-Wavenet-C'*) and 4 male voices (*'en-US-Wavenet-D'; 'en-US-News-N'; 'en-US-Wavenet-I'; 'en-US-News-M'*). Prior to generating the audio speech for the noise, we set the f0 parameter for each voice as follows. For all voices we used the vowel /ɑ/ as a reference (Cristina Oliveira et al., 2021; De Krom, 1994), then for each voice we measured the original f0 of the voice for the duration of this vowel using the built-in function 'pitch' of Matlab (R2022b; The MathWorks Inc.) and time windows of 52 ms., and we defined the f0 as the median of the f0 measured for all time windows. We then calculated by how much we should increase or decrease the original f0 of the voice to get to the custom f0 we wanted.

After generating the 24 audio sentences for each of the 8 voices, we created the multi-talker noise stimuli using custom Matlab codes, closely following the method of (Van Engen & Bradlow, 2007): 1) Each audio track was normalized to have the same RMS amplitude across all tracks; 2) For each talker, two randomly chosen sentences were concatenated to ensure the duration of the noise tracks would exceed the durations of all target sentences; 3) A random multiple of 100 ms (0–500 ms) of silence was added at the beginning of each concatenated sentences to stagger the talkers once they were mixed together; 4) All eight talkers were mixed, by randomly choosing one concatenated sentence by talker, and the initial 500 ms of the concatenated sentences was removed

to eliminate noise that did not contain all eight talkers; 5) The first 100 ms of the complete noise tracks was faded in. In total, we produced 120 multi-talker noise stimuli. In a final step, we mixed the fifth sentences of each of the previously generated conversations or each of the one-sentence stimuli with a randomly chosen noise stimulus for the entire duration of the sentences. Here, the level of the multi-talkers masking sound was held constant, while the amplitude of the target stimuli was decreased by SNRs of -1, -4, and −6 dB, where -4 and -6 are known to produce a speech reception threshold (see Plomp & Mimpen, 1979) that is in the range of 40% to 60% depending on the studies and methods (Brungart et al., 2001; Dingemanse & Goedegebure, 2020; Festen & Plomp, 1990; Hagerman, 1984; McArdle et al., 2005; Miller et al., 1951). These values were also tested in prior in-the-lab pilot testing (unpublished data) to estimate a range of SNRs that would adequately capture the skill level of young healthy participants, while limiting floor or ceiling effects as well as subject frustration (Coffey et al., 2019).

D. Procedure. All experiments were developed using PsychoPy (Peirce et al., 2019), then transformed into JavaScript using the PsychoJS library, as implemented in PsychoPy, and hosted on the Pavlovia platform (*www.pavlovia.org*) for online running of the experiments. Participants were then recruited on the Prolific platform (*www.prolific.com*) and the study was restricted only to people with a desktop computer or a laptop. Prior to enrolling in the study, online participants were instructed that wearing headphones or earbuds was mandatory to participate. They were also asked to be in a silent and calm environment, as well as remove any object around them that may disturb their attention, such as a smartphone or a TV.

Prior to beginning the study, participants went through a series of checks to ensure optimal ‘auditory hygiene’ while performing the tasks. To do so, we used guidelines and scripts from (Zhao et al., 2022). More specifically, participants first heard multi-talker babble noise alone without

target sentences and they were instructed to adjust their audio volume at a comfortable level, so they would not be exposed to overly loud sounds during the experiment. They then performed a headphone screening using Antiphase tone (Woods et al., 2017) to confirm that they were wearing headphones. More specifically, for this task participants had to correctly detect an acoustic target in an intensity-discrimination task. On each trial, they were presented with three consecutive 200 Hz sinusoidal tones in random order, and they were asked to determine which of the tones was perceptually the softest. Two of the tones were presented diotically: 1) the 'standard', and 2) the 'target' that was presented at -6 dB relative to the standard. The third tone (the 'foil') had the same amplitude as the standard but was presented dichotically such that the left and right signals had opposite polarity (anti-phase, 180°). Over headphones, the standard and foil should have the same loudness, making the target clearly distinguishable as softer. In contrast, over loudspeakers the left and right signals interact destructively before reaching the listener's ears, resulting in a weaker acoustic signal at both ears, and thus a weaker loudness sensation for the foil than the target, causing participants to respond incorrectly. Following the headphone check, participants had to read and sign electronically the consent form, after which they were allowed to participate in the study.

Each experiment (for which specific differences will be given below) was preceded by a training task of 6 trials. For each training task, sentence-in-noise SNRs were of -1 dB for the first half of the stimuli and of -4 dB for the second half, while each training trial was followed by feedback. Each experiment consisted of two main tasks: 1) a baseline task, in which only one-sentence stimulus were presented in noise, that was used to assess the level of understanding of sentences-in-noise for each participants without prior social or semantic context given and 2) a conversational task, in which dialogues or monologues in intact or sentence-scrambled order were

presented, with the fifth sentences of each stimuli embedded in noise, that was used to assess the effects of prior social or semantic context given on the processing of sentences embedded in noise. For both tasks, immediately after hearing a sentence in noise, the participants heard it again but without noise. Half of the time, these repeated sentences were exactly the same as the one presented with noise, while the other half had a one-word difference. The task for the participant was to determine, as quickly as possible, whether the repeated sentence was exactly the same or different than the one presented in noise, using the left or right arrows on their keyboard.

A typical trial began with a waiting time of 500 ms. with a fixation cross at the center of the screen, followed by the presentation of the auditory stimuli, then by a visual reminder of the response buttons until the participants pressed one of the two buttons, and afterwards it began again. Every 32 trials, the participants were invited to take a break. The response buttons were counterbalanced across participants (i.e., half of the participants used the left arrow for the 'same' trials and right arrow for the 'different' trials, while the other half did the opposite). The first voice heard was also counterbalanced across participants (i.e., half heard the female voice first in the first presented stimuli, while the other half heard the male voice in first). For all tasks, the order of trials was pseudo-randomized to avoid the presentation of more than 3 of the same trial type (same/different), target voice (male/female), social factor (dialogue/monologue), semantic factor (intact/scrambled) or SNR (-4/-6 dB; for Exp. 1 only).

At the end of the experiment, participants completed the 50-item Autism-Spectrum Quotient scale (AQ; Baron-Cohen et al., 2001) which measures the degree to which an adult with normal intelligence shows traits associated with the ASD (Autistic Spectrum Disorders), in the domain of social skills, attention-switching, attention to details, communication, and imagination. Subjects responded to each item using a 4-point rating scale, ranging from "definitely agree" to

"definitely disagree". Calculation of the AQ quotient was performed following the instructions provided by Baron-Cohen et al. (2001). Here, higher scores indicate greater ASD traits while lower scores indicate fewer ASD traits.

All responses (Accuracy, reaction time [RTs] and AQ questionnaire) were collected with Pavlovia and processed with Matlab.

E. Data preprocessing. For all experiments, the following data preprocessing steps were applied: 1) Participants were excluded from the study if their average accuracy in the baseline task was less than 24 correct out of 44 trials (54.5%), meaning they were not able to do the experiment correctly, that could be due to various reasons (e.g., low quality headphones, low volume, noisy environment, inattention etc.) We note that this criterion of 24 correct out of 44 trials (54.5%) was defined *a priori* because we wanted to keep only the participants that were correctly able to perform the task. Thus, we considered that a lower criterion would have been too weak to assess it; 2) For each participant, trials for which RTs were >3 SD above the participant mean were discarded for both RTs and Accuracy; 3) For each participant, trials in which the participant's response was inaccurate were discarded for RTs only; 4) For each participant, both Accuracy and RTs mean performances for each condition were baseline corrected using the baseline performance measured in the baseline task using this formula: [(Performance-Baseline)/Baseline]. The baseline corrected measures were then multiplied by 100 and performances were assessed as percent changes as compared to the baseline. This correction was done to take into account inter-subject variability in performing the task (i.e., some participants may overall perform better or worse than other at our task, irrespective of the context provided); 5) Participants were excluded from the study if their mean normalized RTs averaged across all conditions was >3 SD above the group mean.

F. Analyses. For all experiments, baseline corrected mean Accuracy (mean proportion of correct responses) and mean RTs were used to compare the effect of intact vs. scrambled conversation across dialogues and monologues. To do so, for experiment 1 we used a Mixed-Model ANOVA (between factor: social context; within factor: semantic context). For the three other experiments, we used repeated-measures ANOVAs with two factors: social context (Dialogue/Monologue) x semantic context (Intact/Scrambled). Post-hoc analyses were performed using pairwise *t* tests (two-tailed).

III. EXPERIMENT 1

A. Goal. Experiment 1 was conducted to choose a correct SNR for measuring our effects of interest in the subsequent experiments. To do so, based on prior in-the-lab pilot studies we selected two SNRs of -6 and -4 dB.

B. Participants. Experiment 1 included two subgroups, with one group presented with dialogues only and one group presented with monologues only. Group 1 was composed of 37 participants (10 female, 2 sex undetermined, mean age 28.7 years +/- 5.92 SD) after exclusion of 3 participants. Group 2 was composed of 33 participants (13 female, 1 sex undetermined, mean age 30.9 years +/- 6.4 SD) after exclusion of 7 participants. Exclusion of participants was based on the criteria given in the method before.

C. Stimuli. For each subgroup, half or the unique stimuli were presented with an SNR of -6dB, while the other half was presented with and SNR of -4dB, and stimuli were randomly assigned in one or the other half for each participant.

D. Procedure. For the two groups, the experiment began with two training tasks: one with 8 baseline trials and the other with 4 conversation trials. The order of the training tasks was

counterbalanced over participants. Following the training, participants underwent the experiment that consisted of two baseline blocks (32 trials each) and two conversation blocks (32 trials each) interleaved, for which the order was counterbalanced across participants.

E. Results. For the SNR of -6 dB we found a mean baseline accuracy of 61.9 % (+/- 1.9 SEM) for group 1 and 64.5 % (+/- 1.8 SEM) for group 2, while for the SNR of -4 dB, we found a mean baseline accuracy of 73.2 % (+/- 1.8 SEM) for group 1 and 72.3 % (+/- 1.8 SEM) for group 2. For the main task, prior to apply baseline correction, for the SNR of -6 dB we found a mean average accuracy of 61.7 % (+/- 1.8 SEM) for group 1 and 60.2 % (+/- 1.9 SEM) for group 2, while for the SNR of -4 dB we found a mean average accuracy of 78.1 % (+/- 1.8 SEM) for group 1 and 77.1 % (+/- 1.5 SEM) for group 2.

After applying the baseline correction, for the SNR of -6 dB (fig. 2a), neither RTs nor Accuracy showed any effect at all for the two factors. The mixed-model ANOVA for RTs showed no effects of social ($F(1,68) = 2.07$, $p = 0.154$, $np2 = 0.03$) or semantic context ($F(1,68) = 2.56$, $p = 0.114$, $np2 = 0.04$), and no interaction between the two ($F(1,68) = 0.04$, $p > 0.250$, $np2 = 0.01$). The mixed-model ANOVA for accuracy showed no effects of social ($F(1,68) = 1.36$, $p = 0.248$, $np2 = 0.02$) or semantic context ($F(1,68) = 0.47$, $p > 0.250$, $np2 = 0.01$), and no interaction between the two ($F(1,68) = 0.76$, $p > 0.250$, $np2 = 0.01$). For the SNR of -4 dB (fig. 2b), using RTs the mixed-model ANOVA showed no effect of social context ($F(1,68) = 0.55$, $p > 0.250$, $np2 = 0.01$), but a trend for an effect of semantic context ($F(1,68) = 3.81$, $p = 0.055$, $np2 = 0.05$). There was no interaction between the two factors ($F(1,68) = 2.20$, $p = 0.143$, $np2 = 0.03$). Post-hoc *t*-tests showed lower RTs for intact vs. sentence-scrambled conversations for monologues, but no differences for dialogues (Dialogues: $t(36) = 0.33$, $p > 0.250$; Monologues: $t(32) = 2.52$, $p = 0.017$). Using Accuracy, the mixed-model ANOVA showed no effects of social ($F(1,68) = 0.01$, $p > 0.250$, *np2*

= 0.01) or semantic context ($F(1,68) = 0.33$, $p > 0.250$, $np2 = 0.01$). However, interestingly, it showed a trend for an interaction between these two factors ($F(1,68) = 3.80$, $p = 0.055$, $np2 = 0.05$), reflecting a larger difference between intact and scrambled conversations for monologues as compared to dialogues. Post-hoc unpaired *t*-tests showed higher Accuracy for intact vs. sentence-scrambled conversations for dialogues, but no differences for monologues (Dialogues: $t(36) = 2.10$, $p = 0.043$; Monologues: $t(32) = 0.84$, $p > 0.250$).

To summarize, prior to baseline correction we first found that an SNR of -6 dB was producing accuracies in the range of 60-65%, while an SNR of -4 dB was producing accuracies in the range of 72-78%, that was a first indication that an SNR of -6 dB might be too close to chance level, while and SNR of -4 might be appropriate for our means. After applying the baseline correction, we see that an SNR of -6 (fig. 2a) produces accuracies for sentences in whole conversations that are in the same range of accuracy that for the individual baseline sentences (i.e., the percent signal change accuracies for sentences in conversations after baseline correction is close to or below 0). Thus, this showed clearly that an SNR of -6 was too low to measure potential perceptual gain that could be due to the context manipulation of the whole conversation. On the contrary, after baseline correction we see that for every condition an SNR of -4 (fig. 2b) produces percent signal change accuracies for sentences in whole conversations that are clearly above 0, meaning that this SNR could permit to measure potential perceptual gain that could be due to the context manipulation of the whole conversation. In addition, we found that using an SNR of -6 dB showed no effects at all neither for RTs or Accuracy, while using an SNR of -4 dB showed some effects for both RTs and Accuracy. For all these reasons, we used an SNR of -4 dB for all subsequent experiments.

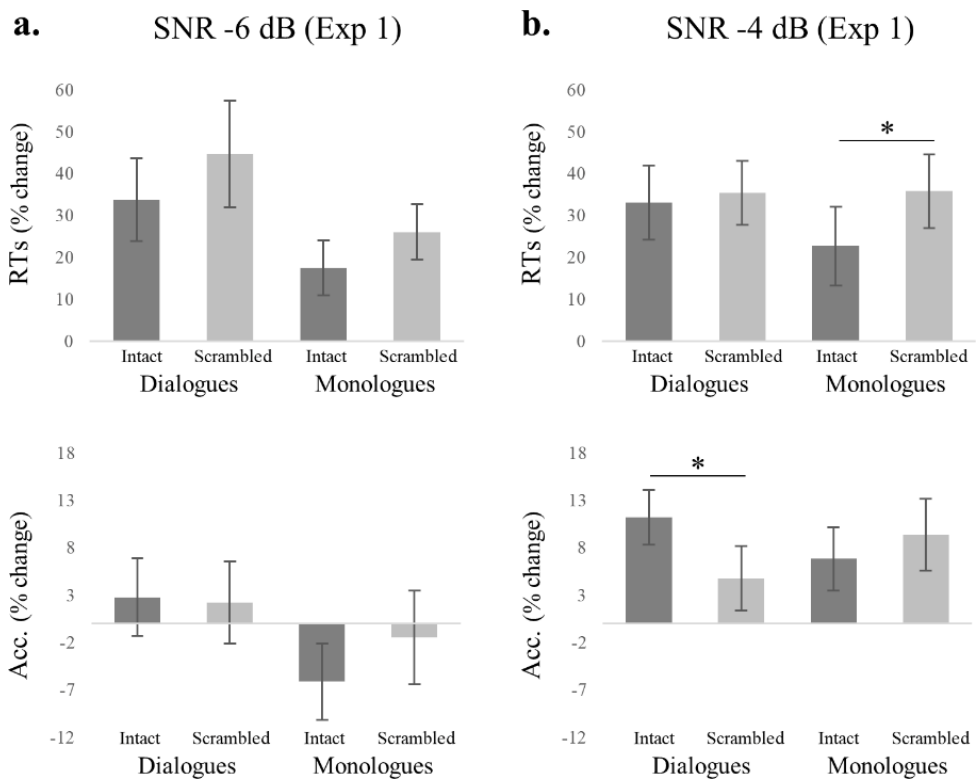


Figure 2. RTs and Accuracy for experiment 1. Percent signal change from baseline for Response times (RTs) and proportion of correct responses (Accuracy) for intact and scrambled dialogues or monologues with SNRs of (**a.**) -6 dB and (**b.**) -4 dB. *$p \leq 0.05$.

IV. EXPERIMENT 2

A. Goal. Experiment 2 was specifically designed to address the effect of semantic context while controlling for the effect of social context. We hypothesized that the predictive nature of intact conversations, which includes semantic coherence at the large scale of a conversation, would facilitate speech processing as compared to sentence-scrambled one. To do so, within a same block we randomly presented both intact and scrambled conversations, while a same block was composed with only dialogues or only monologues, and all conditions was presented to the same participants across several blocks. Here, we expected to find a main effect of semantic context using the repeated measures ANOVA.

B. Participants. Experiment 2 was composed of 70 participants (28 female, 2 sex undetermined, mean age 31.7 years +/- 5.83 SD) after exclusion of 4 participants based on the criteria given in the method before.

C. Stimuli. For each participant, half of the unique stimuli was presented in the dialogue condition and repeated across the intact and scrambled conditions while the other half was presented in the monologue condition and repeated across the intact and scrambled conditions, and stimuli were randomly assigned in one or the other half for each participant.

D. Procedure. Experiment 2 used an SNR of -4 dB and began with the baseline task. More specifically, at first a training task featuring 6 baseline trials was followed by a testing task of 44 baseline trials. If a participant failed more than 54.5% of the baseline trials, she or he was excluded from the study. Afterwards, participants were presented with one block of dialogues only and one block of monologues only (32 trials each, with half intact and half sentence-scrambled conversations, presented in random order). The order of blocks was counterbalanced across participants. Each block was preceded by a training task of 4 trials of the same condition.

E. Results. Using RTs, the repeated measures ANOVA showed no effect of social context ($F(1,69) = 0.40$, $p > 0.250$, $np2 = 0.01$), but a main effect of semantic context ($F(1,69) = 10.74$, $p = 0.002$, $np2 = 0.13$), with no interaction between these two factors ($F(1,69) = 0.02$, $p > 0.250$, $np2 = 0.01$). Post-hoc *t*-tests (fig. 3a) showed lower RTs for intact vs. sentence-scrambled conversations for both dialogues and monologues (Dialogues: $t(69) = 2.68$, $p = 0.009$; Monologues: $t(69) = 2.38$, $p = 0.020$).

Using Accuracy, the repeated measures ANOVA showed no effects of social ($F(1,69) = 0.80$, $p > 0.250$, $np2 = 0.01$) or semantic context ($F(1,69) = 1.46$, $p = 0.231$, $np2 = 0.02$), and no interaction between the two ($F(1,69) = 0.02$, $p > 0.250$, $np2 = 0.01$).

V. EXPERIMENT 3

A. Goal. Experiment 3 was specifically designed to address the effect of social context while controlling for the effect of semantic context. We hypothesized that the interactive nature of dialogues, which includes turn-taking and dynamic exchanges, would create a richer social context, thereby facilitating speech processing as compared to monologues where these cues are absent. To do so, within a same block we randomly presented both dialogues and monologues, while a same block was composed with only intact or scrambled conversations, and all conditions was presented to the same participants across several blocks. Here, we expected to find a main effect of social context using a repeated measures ANOVA.

B. Participants. Experiment 3 was composed of 59 participants (21 female, mean age 32.1 years +/- 5.81 SD) after exclusion of 7 participants based on the criteria given in the method before.

C. Stimuli. For each participant, half of the unique stimuli was presented in the intact condition and repeated across dialogues and monologues while the other half was presented in the scrambled condition and repeated across dialogues and monologues, and stimuli were randomly assigned in one or the other half for each participant.

D. Procedure. Experiment 3 used an SNR of -4 dB and began with the baseline task. More specifically, at first a training task featuring 6 baseline trials was followed by a testing task of 44 baseline trials. If a participant failed more than 54.5% of the baseline trials, she or he was excluded from the study. Afterwards, participants were presented with one block of intact conversations

only and one block of sentence-scrambled conversation only (32 trials each, with half dialogues and half monologues presented in random order). The order of blocks was counterbalanced across participants. Each block was preceded by a training task of 4 trials of the same condition.

E. Results. Using RTs, the repeated measures ANOVA showed a trend for an effect of social context ($F(1,58) = 2.85$, $p = 0.097$, $np2 = 0.05$), no effect of semantic context ($F(1,58) = 0.32$, $p > 0.250$, $np2 = 0.01$), and no interaction between these two factors ($F(1,58) = 0.22$, $p > 0.250$, $np2 = 0.01$). Post-hoc *t*-tests (fig. 3b) showed no differences of RTs for dialogue vs. monologues for both intact and scrambled conversations (Intact: $t(58) = 0.84$, $p > 0.250$; Scrambled: $t(58) = 1.52$, $p = 0.134$).

Using Accuracy, the repeated measures ANOVA showed no effects of social context ($F(1,58) = 0.01$, $p > 0.250$, $np2 = 0.01$) but an effect of semantic context ($F(1,58) = 8.62$, $p = 0.005$, $np2 = 0.13$), and no interaction between these two factors ($F(1,58) = 0.01$, $p > 0.250$, $np2 = 0.01$). Post-hoc *t*-tests showed higher accuracy for intact vs. scrambled conversations for dialogues and a trend for this effect for monologues (Dialogues: $t(58) = 2.18$, $p = 0.034$; Monologues: $t(58) = 1.91$, $p = 0.062$).

VI. EXPERIMENT 4

A. Goal. Experiment 4 was specifically designed to address both the effects of semantic and social context at the same time. To do so, within a same block we randomly presented all conditions (i.e., both dialogues and monologues in both intact and sentence-scrambled orders), and all conditions was presented to the same participants across several blocks. Here, we expected to find both effects of social and semantic contexts using the repeated measures ANOVA, and potentially an interaction between these two factors.

B. Participants. Experiment 4 was composed of 68 participants (36 female, 1 undermined, mean age 29.7.1 years +/- 5.5 SD) after exclusion of 7 participants based on the criteria given in the method before.

C. Stimuli. For each participant, half of the unique stimuli were presented in the dialogue condition and repeated across the intact and scrambled conditions while the other half were presented in the monologue condition and repeated across the intact and scrambled conditions, and stimuli were randomly assigned in the other half for each participant.

D. Procedure. Experiment 4 used an SNR of -4 dB and began with two training tasks: one with 8 baseline trials and the other with 4 conversation trials. The order of the training tasks was counterbalanced over participants. Following the training, participants underwent the experiment that was constituted of two baseline blocks (32 trials each) and two conversation blocks (32 trials each) interleaved, for which the order was counterbalanced across participants.

E. Results. Using RTs, the repeated measures ANOVA showed effects of both social ($F(1,67) = 5.39$, $p = 0.023$, $np2 = 0.07$) and semantic context ($F(1,67)= 10.12$, $p = 0.002$, $np2 = 0.13$), but no interaction between these two factors ($F(1,67) = 1.17$, $p > 0.250$, $np2 = 0.02$). Here, we conducted an additional one-way repeated measure ANOVA to compare the mean RTs across all four experimental conditions (Intact Dialogues, Scrambled Dialogues, Intact Monologues, Scrambled Monologues). We found that mean RTs were significantly different from each other ($F(3,268)= 4.95$, $p = 0.002$, $np2 = 0.05$). Critically, post-hoc *t*-tests (fig. 3c) showed that these differences were largely driven by the intact dialogues for which RTs were significantly lower than every other conditions (*vs.* scrambled dialogues: $t(67) = 3.03$, $p = 0.004$; *vs.* intact monologues: $t(67) = 3.06$, $p = 0.003$; *vs.* scrambled monologues: $t(67) = 4.44$, $p < 0.001$).

Using Accuracy, the repeated measures ANOVA showed no effects of social context ($F(1,67) = 1.94$, $p = 0.168$, $np2 = 0.03$) or semantic context ($F(1,67) = 1.56$, $p = 0.216$, $np2 = 0.02$), and no interaction between these two factors ($F(1,67) = 2.07$, $p = 0.155$, $np2 = 0.03$).

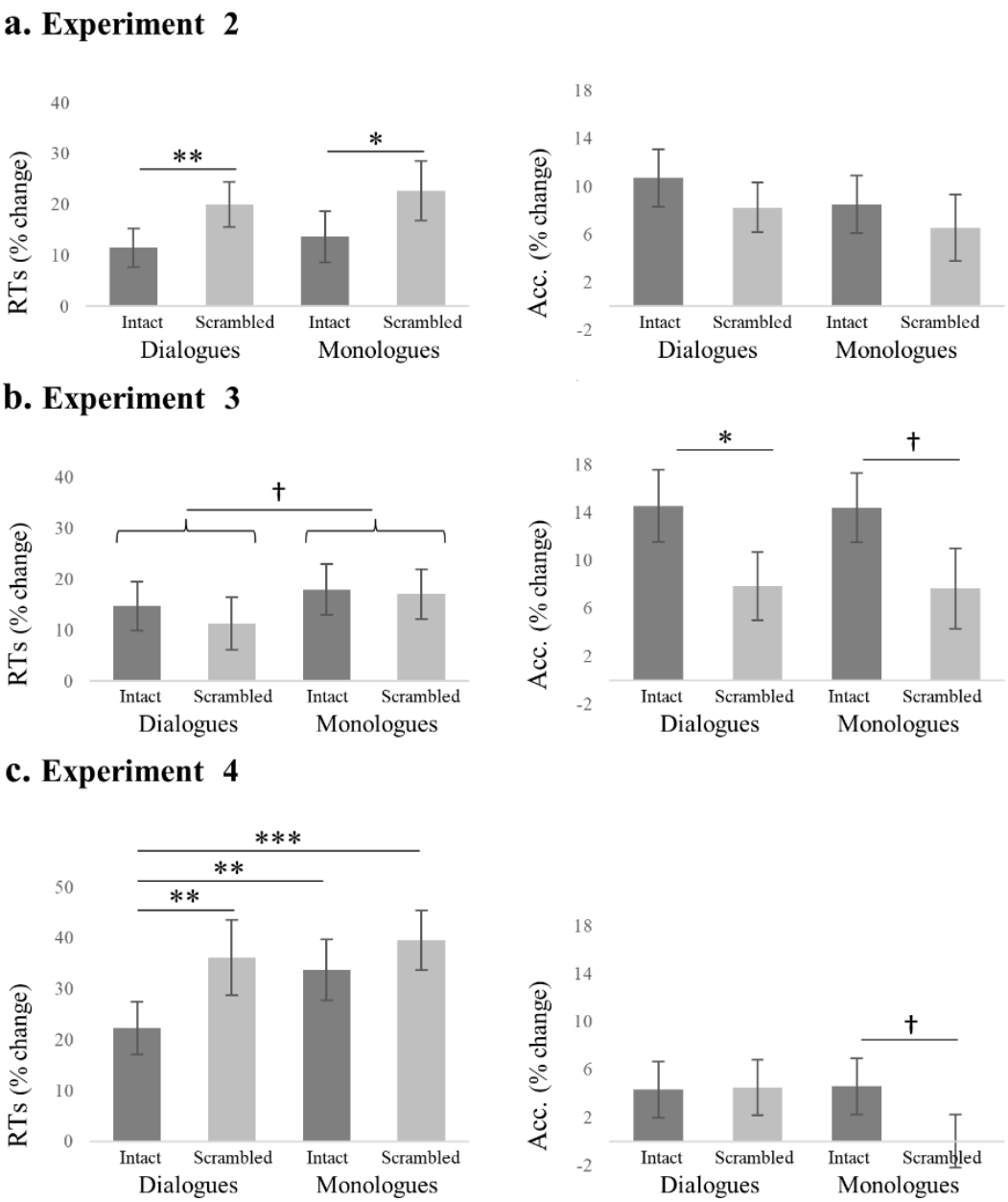


Figure 3. Behavioral data for experiments 2, 3 and 4. Percent signal change from baseline for Response times (RTs) and proportion of correct responses (Accuracy) for intact and scrambled dialogues and monologues for experiments 2 (**a.**), 3 (**b.**) and 4 (**c.**). †p ≤ 0.10; *p ≤ 0.05; **p ≤ 0.01; ***p ≤ 0.001.

VII. COMBINED EXPERIMENTS

A. Goal. Here, we combined the data of experiments 2, 3 and 4, that have the exact same conditions for each participant, to increase the statistical power of our analyses.

B. Participants. The participants were the same as in experiment 2, 3 and 4, except that we excluded all participants for which RTs averaged across all conditions was >3 SD above the combined group mean. Thus, the combined experiment was composed of 193 participants after exclusion of 4 participants.

C. Results. Using RTs, the repeated measures ANOVA showed effects of both social ($F(1,192) = 8.52$, $p = 0.004$, $np2 = 0.04$) and semantic context ($F(1, 192)= 10.01$, $p = 0.002$, $np2 = 0.05$), but no interaction between these two factors ($F(1, 192) = 0.13$, $p > 0.250$, $np2 = 0.01$). Here, we conducted an additional one-way repeated measure ANOVA to compare the mean RTs across all four experimental conditions (Intact Dialogues, Scrambled Dialogues, Intact Monologues, Scrambled Monologues). We found that mean RTs were significantly different from each other ($F(3,768)= 6.97$, $p < 0.001$, $np2 = 0.03$). Critically, post-hoc *t*-tests showed that these differences were largely driven by the intact dialogues for which RTs were significantly lower than every other conditions (*vs.* scrambled dialogues: $t(192) = 2.37$, $p = 0.019$; *vs.* intact monologues: $t(192) = 2.27$, $p = 0.024$; *vs.* scrambled monologues: $t(192) = 4.45$, $p < 0.001$).

Using Accuracy, the repeated measures ANOVA showed no effect of social context ($F(1, 192) = 2.04$, $p = 0.155$, $np2 = 0.01$), but an effect of semantic context ($F(1, 192)= 11.17$, $p = 0.001$, $np2 = 0.05$), and no interaction between these two factors ($F(1, 192) = 0.26$, $p > 0.250$, $np2 = 0.01$). Post-hoc *t*-tests showed higher Accuracy for intact vs. sentence-scrambled conversations for both

dialogues and monologues (Dialogues: $t(192) = 2.04$, $p = 0.042$; Monologues: $t(192) = 2.54$, $p = 0.012$).

To study whether we could find a relationship between performances in processing conversations and individual's social abilities, we performed a Spearman correlation between the individual AQ scores and the individual difference scores for intact minus scrambled conversations, separately for dialogues and monologues. Using RTs, for dialogues (fig. 4b) but not monologues (fig. 4c) we found that there was a negative correlation between AQ and processing of intact vs. scrambled conversations (Dialogues: $rho(197) = -0.18$, $p = 0.010$; Monologues: $rho(197) = 0.07$, $p > 0.250$). Furthermore, we found that these two correlations were significantly different from each other ($p = 0.008$) using a percentile bootstrap approach (Wilcox, 2016). We didn't find significant correlations using Accuracy (Dialogues: $rho(197) = -0.03$, $p > 0.250$; Monologues: $rho(197) = 0.08$, $p > 0.250$) with no differences between dialogues and monologues ($p < 0.250$).

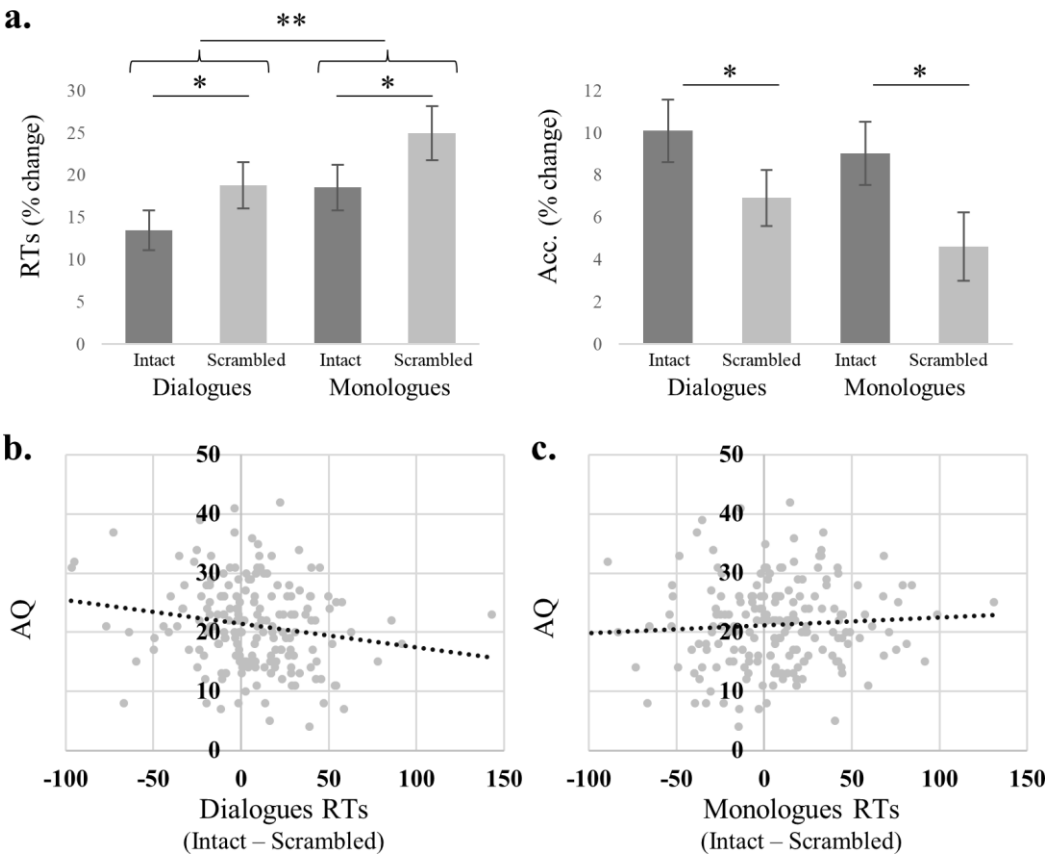


Figure 4. Behavioral data for combined experiments. a. Percent signal change from baseline for Response times (RTs) and proportion of correct responses (Accuracy) for intact and scrambled dialogues and monologues for combined experiments (exp. 2, 3 and 4). *$p \leq 0.05$; **$p \leq 0.01$. **b. c.** Spearman correlation between the individual AQ scores and the individual difference scores for intact minus scrambled dialogues (b) and monologues (c).

VIII. DISCUSSION

The present study was designed to investigate the processing of multiple-speaker conversations from a third-person perspective through a set of four experiments. The first experiment was designed to choose the correct SNR to be used in subsequent experiments, that was set to -4 dB. The second experiment was designed to assess specifically the effect of semantic context, and showed this effect on response time only, but no effect of social context in either response time or accuracy. The third experiment was designed to assess specifically the effect of

social context and showed a trend for this effect on response time only, as well as a significant effect of semantic context in accuracy only. The fourth experiment was designed to assess both the effect of semantic and social context at the same time and showed both effects on response times only. Combined data from experiment two, three and four showed effects of both semantic and social context on response times, and an effect of semantic context on accuracy only. They also showed that the processing of dialogues, but not monologues, was correlated with an individual score of social traits.

Our finding that semantically related information can facilitate the understanding of spoken speech in the presence of masking sound is in line with previous studies that showed similar effects using a variety of approaches (Golestani et al., 2009, 2013; O'Neill et al., 2021; Roland et al., 2012; Zekveld et al., 2011, 2012, 2013). However, even though speech patterns at different timescales are processed using different mechanisms and/or brain regions (DeWitt & Rauschecker, 2012; Farbood et al., 2015), only few studies examined the effects of semantics in the context of an entire conversation; instead, most of them only examined the effects of semantics in isolated words or sentences. Here, we addressed this question using a more naturalistic approach at the larger timescale of a conversation. Thus, although we found that, similarly to isolated words or sentences, there is a significant effect of semantic context when processing sentences embedded in whole conversation, an open question is whether these effects are relying on the same mechanisms and/or brain regions than for shorter timescales. Overall, our finding is coherent with what one might expect within a predictive coding framework (Clark, 2013; Friston, 2005; Rao & Ballard, 1999). Indeed, within this framework, it is believed that accurate prior knowledge leads to a reduction in error signal between top-down predictions and bottom-up sensory information, which results in perceptual enhancement and an overall change in neural activity (Sohoglu et al.,

2012). Note however that the effect we measured was not trivially due to detecting a semantic anomaly in the altered sentence, because the changed word always resulted in a semantically appropriate sentence. Thus, the predictive mechanism is operating at a more abstract level, perhaps related to sentence cohesion, than at a more local level of single-word error detection.

Furthermore, the fact that, under at least some circumstances, an individual is quicker and better at correctly processing a sentence in the context of a dialogue as compared to a monologue is in keeping with the idea that the human perceptual system is tuned to socially relevant stimuli (Belin et al., 2000; Issard et al., 2023; Levy et al., 2003). However, while previous research consistently showed that people are better at understanding dialogues than monologues (Branigan et al., 2011; Fox Tree, 1999; Tolins et al., 2018), this effect has been usually linked to the internal content of a dialogue as compared to a monologue, rather than to its intrinsic social value as an interaction. Indeed, dialogues usually contain information that monologues lack, such as discourses markers and/or different perspectives from multiple interlocutors, that may help in the understanding of the information that is shared (Pickering & Garrod, 2021). While this hypothesis may provide a partial explanation for this advantage in certain situations, it cannot apply to our study. Here, we used the exact same contents for both dialogues and monologues, with the only change being the sex of the speakers (voice timbre) and their alternation or not. Furthermore, our task required the listener to identify if a word had been changed, but that word was not itself relevant to the content of the dialogue (e.g., see figure 1, in which the changed word was “true” vs “pure” both of which fit the meaning of the sentence, and neither of which is related to the dialogue content). Thus, we rather hypothesize that the presence of social cues, such as two speakers interacting with each other, would trigger a sharpening of the content of sentences by the perceptual system, that we observed for dialogues but not monologues. This account suggests in

turn that dialogues would provide additional cognitive engagement through social cues such as turn-taking and speaker interaction, which are absent in monologues. Hence, dialogues, due to their interactive nature, would create a richer social context that enhances speech processing. This hypothesis is in line with recent findings in the domain of visual perception showing that a human body is better perceived when facing another body (i.e., such as in a social interaction) as compared to facing in an opposite direction (Abassi & Papeo, 2023; Papeo et al., 2017; Papeo & Abassi, 2019; Vestner et al., 2019, 2021).

In addition, we found that the processing of dialogues, but not monologues, correlates with individual autism-spectrum traits, so that the magnitude of the difference in performances between intact and scrambled dialogues decreases as the AQ score increases. In the auditory modality, some correlations between perceptual performance for processing social stimuli and autistic traits has been found for voice recognition (Gervais et al., 2004; Schelinski et al., 2016; Skuk et al., 2019) and phonetic categorization (Stewart & Ota, 2008), but wasn't yet found for the processing of sentences. In the visual modality, such correlations have been found for the processing of faces (Wyer et al., 2012), biological motion (van Boxtel et al., 2017) or animals (Yang et al., 2024), but also for processing two bodies engaged in a prototypical interaction (Abassi & Papeo, 2022). The results of this last study strongly echo the results that we found in the current study, in the sense that they both show a correlation between perceptual processing of social interactions and individual social abilities, independently of the visual or auditory modality. This raise the question of whether the influence of social traits on processing social stimuli is linked to the perceptual modality in itself or would rather be linked to a domain-general mechanisms that would be generally involved in processing social interactions, independently to the modality. While further experiments will be needed to approach this question, behavioral effects that reliably characterize

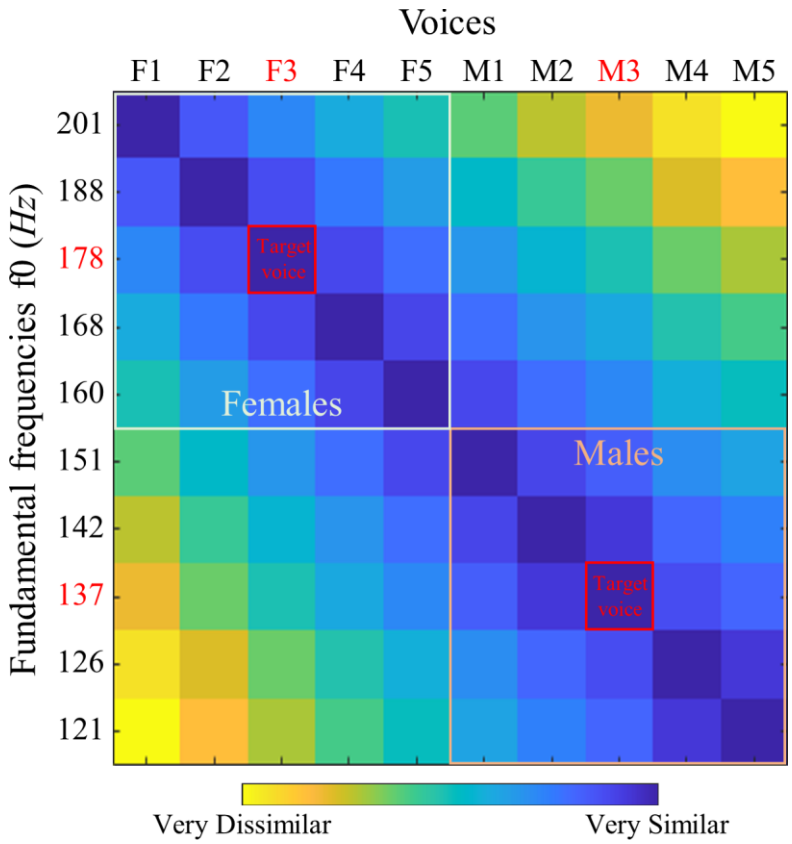
the performance of the individual, highlighting population-level and interindividual differences (see also Pesquita et al., 2022), appear especially worthy of attention as they can offer handy tools for detection of developmental disorders or vulnerabilities.

Overall, another point to highlight is that effects of social context were found only with RTs, while effects of semantic context were found in both RTs and accuracy. A first reason for this difference may be that our task could be more fine-tuned (e.g., by using an adaptative SNR; see Soleymani et al., 2019) to better take into account individual variabilities that would be reflected in performance on the task and especially accuracy, that is more sensitive to floor or ceiling effects than RTs (Magnus et al., 2017; Willoughby et al., 2023). Another reason could be due to the nature of the measured effects themselves. Indeed, it has been proposed that RTs and accuracy may be affected by different attentional cues via distinct cognitive and/or neural mechanisms (Prinzmetal et al., 2005; van Ede et al., 2012 but see Mulder & Van Maanen, 2013). Thus, effects of social and semantic contexts may rely on different attentional cues, that may be reflected in measuring RTs and accuracy, while the exact nature of these cues, if they exist, would need a more thorough exploration. A last point is that, while we found both effects of social and/or semantic contexts depending on the design of our experiments, we never found an interaction between these two factors. Although this is not a limitation in itself, previous literature showed a strongest perceptual sensitivity for stimuli implying multiple interactors as compared to stimuli with individuals, at least in the visual system (Isik et al., 2017; Walbrin & Koldewyn, 2019). Thus, we would have expected to find that the difference of performance in processing intact versus scrambled conversations would be higher for dialogues than monologues. Previous attempts to find an analogous interaction in the brain have been so far unconclusive (Landsiedel & Koldewyn, 2023; Olson et al., 2023), so this interaction, if it exists, has yet to be found.

Another hypothesis that could explain our lack of interaction between semantic and social factors is that while our study was designed to isolate the effects of social context by using identical content in both monologue and dialogue conditions, there could be a potential for unintended semantic influences, as it is atypical for a single speaker to carry on both sides of a conversation. This could have unintended consequences, influencing the processing or monologues differently than dialogues but partly due to some semantic factors instead of social factors only. However, our choice of experimental design was essential to distinguish the impact of social interaction cues from semantic content. Indeed, the monologue condition, though unconventional, effectively created a different social context characterized by the absence of interaction cues, and this approach allowed us to focus on how turn-taking and dynamic exchanges in dialogues enhance speech processing. Thus, although the monologue condition could introduce some unexpected semantic incoherences, we believe that the differences in speech processing we observed primarily reflect the presence or absence of social interaction cues. Indeed, the task for listeners remained consistent across all conditions, ensuring that any variance in performance was attributable to social dynamics rather than semantic content. Future studies could further refine this approach to better disentangle these factors, but in the context of our current study, the primary findings support the influence of social interaction on auditory perception. As a last point, we also highlight that in the current study we found the lowest RTs in processing intact dialogues as compared to every other condition in some experiments. This finding, alongside the presence of a correlation between processing dialogues and autistic traits, provides clues for the existence of special mechanisms in processing canonical verbal social interactions between multiple interactors as compared to other forms of speech conditions.

To conclude, by exploring the influence of social and semantic contexts on speech perception in naturalistic social scenarios, the present research contributes valuable insights into the intricate interplay between contextual factors (i.e., social and semantic contexts) and hearing performances. Our findings could also have significant practical implications for improving audition in individuals with hearing loss. Indeed, by showing the influence of social and semantic contexts on speech processing at a large-scale level, our results suggest that hearing aid devices may be enhanced to leverage these cues. For instance, incorporating algorithms that take into account dialogue turn-taking and semantic coherence in hearing aid technology could improve speech intelligibility in noisy environments. Furthermore, in sharing our carefully designed set of stimuli, we hope to provide useful materials for further research and/or potential clinical applications. Overall, our findings hold the potential to inform not only our understanding of auditory perception for speech but also the development of interventions and technologies that better align with the complexities of real-world listening experiences for individuals with hearing loss.

IX. SUPPLEMENTARY MATERIALS.



Supplementary Figure 1. Dissimilarity matrix for Euclidean distances between fundamental frequencies of the voices. Captions in red represent the target voices for female (F3) and male (M3). Captions in black represent the concurrent voices of females (F1, F2, F4, F5) and males (M1, M2, M4, M5) that are used in the multi-talker babbling noise.

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XI. AUTHOR DECLARATIONS. All authors declare that they have no financial or non-financial conflict of interests to disclose. They also declare that all procedures used in the current study were performed in compliance with the code of ethics of the World Medical Association's

Declaration of Helsinki and have been approved by the Faculty of Medicine Institutional Review Board of McGill University on the 3rd of October 2022 (reference number: A08-B75-22B / 22-07-116).

XII. DATA AVAILIBILITY. The entire set of stimuli used in the current study can be found online at www.zlab.mcgill.ca/stimuli/ and can be used under the term of a CC-BY-NC license. The collected data are freely available upon email request to E.A or R.Z.

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