# When AI companions become witty: Can human brain recognize AI-generated irony?

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#### **Abstract**

As Large Language Models (LLMs) are increasingly deployed as social agents and trained to produce humor and irony, a question emerges: when encountering witty AI remarks, do people interpret these as intentional communication or mere computational output? This study investigates whether people adopt the *intentional stance*, attributing mental states to explain behavior, toward AI during irony comprehension. Irony provides an ideal paradigm because it requires distinguishing intentional contradictions from unintended errors through effortful semantic reanalysis. We compared behavioral and neural responses to ironic statements from AI versus human sources using established ERP components: P200 reflecting early incongruity detection and P600 indexing cognitive efforts in reinterpreting incongruity as deliberate irony. Results demonstrate that people do not fully adopt the intentional stance toward AI-generated irony. Behaviorally, participants attributed incongruity to deliberate communication for both sources, though significantly less for AI than human, showing greater tendency to interpret AI incongruities as computational errors. Neural data revealed attenuated P200 and P600 effects for AI-generated irony, suggesting reduced effortful detection and reanalysis consistent with diminished attribution of communicative intent. Notably, people who perceived AI as more sincere showed larger P200 and P600 effects for AIgenerated irony, suggesting that intentional stance adoption is calibrated by specific mental models of artificial agents. These findings reveal that source attribution shapes neural processing of social-communicative phenomena. Despite current LLMs' linguistic sophistication, achieving genuine social agency requires more than linguistic competence, it necessitates a shift in how humans perceive and attribute intentionality to artificial agents.

# **Keywords**

Human-AI interaction; Intentional stance; Irony comprehension; Event-related Potentials; Large Language Models

#### Introduction

Large Language Models (LLMs) have increasingly transformed AI from functional tools into social agents serving as personal assistants, virtual tutors, mental health chatbots, and AI companions (Casu et al., 2024; García-Méndez et al., 2024; Go & Sundar, 2019; Maples et al., 2024). As researchers increasingly train these systems to employ humor and irony for social rapport building (Avetisyan et al., 2024; Ritschel et al., 2019), a critical question emerges: when people encounter witty remarks from AI, do they interpret these as intentional communication or mere computational output?

In daily social interactions, people efficiently navigate their social interaction by explaining and predicting others' behavior with reference to others' mental states; this cognitive strategy is known as adopting the *intentional stance* (Dennett, 1987). For example, when someone says "You are always so punctual!" to a person who arrived late, we naturally assume the speaker intended sarcasm rather than making a factual error. This mental state attribution, as a basic step of Theory of Mind (ToM, Baron-Cohen, 1997; Leslie, 1994), is fundamental to human social cognition and successful communication.

As people increasingly interact with artificial agents, from AI chatbots to companions, the question arises whether they also adopt this intentional stance toward AI systems. Traditional human-computer interaction research has characterized people's tendency to treat computers like real people "mindless anthropomorphism"—automatic attribution of human mental states without considering whether machines actually possess them (Nass & Moon, 2000; Epley et al., 2007). Early evidence supported this view, showing that people processed AI-generated and human-generated irony similarly in behavioral ratings, suggesting they understood AI irony egocentrically without engaging theory of mind processes (Utsumi et al., 2013).

Nevertheless, when machines display greater agency and human-like characteristics, people tend to engage in deliberate inference of mental states using ToM, known as "mindful anthropomorphism" (Gray et al., 2007). Neuroimaging studies demonstrate increased ToM-related brain activation when interacting with more

human-like robots (Krach et al., 2008). Recent behavioral evidence demonstrates that people sometimes explain robot behavior through mental state attribution rather than purely mechanistic explanations (Marchesi et al., 2019). Moreover, people are more likely to attribute mental states to robots when robots exhibit social behaviors such as eye gaze, gestures, and emotional expressions, and when their appearance is more human-like (see Thellman et al., 2022 for a review). These findings leave open critical questions regarding mental state attribution to contemporary AI systems.

Existing evidence derives primarily from robots or simple AI agents rather than human-like conversational AI, powered by LLMs, now widely deployed. While research in human-robot interaction suggest that increased human-likeness may promote mental state attribution, driven by people's need to make sense of and predict agent behaviors (Epley et al., 2007), direct evidence for advanced AI remains lacking. Critically, behavioral methods like self-report are susceptible to social desirability bias and post-hoc rationalization (Braun et el., 2001), meaning participants might say they attribute intention to the AI without their underlying cognitive architecture truly doing so. Therefore, neural evidence is necessary to establish the mechanism. Electroencephalography (EEG) is suited for this due to its millisecond temporal resolution. This allows us to capture the automatic, implicit cognitive processes that unfold as language is being comprehended, revealing whether the brain recruits the same real-time neural signatures (e.g., Event-Related Potentials, ERPs) typically associated with communicative intention in human communication.

Recent neurocognitive evidence reveals that people have developed distinct processing strategies for AI versus human communication, reflecting unconscious adaptation to perceived AI characteristics. This adaptation manifests across semantic and syntactic domains. Reading semantic anomalies attributed to AI elicited a smaller N400 effect relative to human-attributed ones, which implies an anticipation of factual unreliability from AI output. Conversely, AI-attributed syntactic anomalies generate a stronger P600 response relative to human-attributed ones, reflecting people's heightened expectations regarding the grammatical competence of these AI systems (Rao et al., 2024). This source-specific processing extends to social-communicative

contexts. AI-attributed humor produces smaller N400 responses than human-attributed one, indicating reduced cognitive effort during incongruity processing, alongside larger Late Positive Potentials (LPP), suggesting enhanced surprise and emotional reward relative to human-attributed humor. Notably, these processing patterns evolve dynamically as people update their mental models of AI capabilities, evidenced by decreasing N400 and increasing LPP amplitudes over time (Rao et al., 2025). These findings reveal that humans dynamically calibrate their language processing strategies based on continuously revised mental models of AI characteristics. However, whether this neurocognitive adaptation influences intentionality attribution remains unexplored.

Irony comprehension provides an ideal paradigm for examining intentional stance adoption because it requires distinguishing intentional contradictions from unintended errors (Sperber & Wilson, 1981; Utsumi et al., 2013). Processing ironic statements involves effortful reanalysis to determine whether semantic incongruities reflect deliberate meaning or mistakes, a process that should vary systematically with intentional stance adoption. The present study examined behavioral and neural responses to irony from AI versus human sources to investigate whether people adopt the intentional stance towards AI during irony comprehension. We leveraged established ERP components that index different stages of irony processing: P200 reflects early semantic processing and incongruity detection, while P600 reflects effortful semantic reanalysis and meaning integration—the cognitive work of reinterpreting apparent errors as intentional irony (Regel et al., 2010, 2011, 2014; Regel & Gunter, 2017; Spotorno et al., 2013). If people adopt a full intentional stance toward AI, they should show comparable behavioral irony attribution and neural processing patterns for AI and human sources. However, if people adopt a limited intentional stance toward AI, we predicted reduced irony attribution behaviorally, accompanied by smaller P200 and P600 amplitudes for AI compared to human mismatches. Also, given that people's general perceptions of to what extent AI is trustworthiness and sincere modulate the processing of AI humor (Rao et al., 2025), this study also explores whether these perceptions will modulate the intentional stance adoption in comprehending AIgenerated irony.

#### **Methods**

## Design

The study employed a 2 (Type: ironic vs. literal) × 2 (Source: AI vs. human) factorial design. Type was a within-item and within-participants factor. Source was manipulated within items and between participants (AI vs. human), such that participants were told that they would read dialogues either between two humans or between a human and an AI companion (similar to Liu & Sundar, 2018).

# **Participants**

Sixty-four neurologically healthy native Mandarin speakers were initially recruited (28 males; mean age 23 years old, range 18-35). The final sample size was 59 after the exclusion of five participants (see Data recording and preprocessing for details). All participants provided written informed consent and were compensated for their participation. The study received approval from the Joint Chinese University of Hong Kong-New Territories East Cluster Clinical Research Ethics Committee.

#### Materials

We developed 80 sets of Chinese dialogues adapted from Chen et al. (2025) and Weng et al. (2023), each comprising a context utterance by Interlocutor 1 and a comment utterance by Interlocutor 2. The dialogues were distributed across two conditions (ironic vs. literal), with the context utterance manipulated to induce either an ironic or literal interpretation of the identical comment (see Table 1). All target comments followed a fixed syntactic structure with an intensifier preceding a disyllabic adjective (literally translating to "You are really [adjective]"), where the critical words were high-frequency, familiar Chinese disyllabic adjectives. To validate the materials, 20 native Chinese speakers who did not participate in the main experiment rated the degree of irony for all dialogues on a 7-point Likert scale (1 = not at all ironic, 7 = very ironic). Results confirmed that comments in the ironic condition were perceived as ironic (M = 6.59, SD = 0.22), whereas those in the literal condition were not (M = 1.59, SD = 0.32).

Following a Latin Square design, we constructed two stimulus lists, each containing 40 ironic and 40 literal dialogues, with each dialogue set appearing in only one condition per list. Each list also included 80 filler dialogues featuring neutral, non-evaluative exchanges (e.g., Interlocutor 1: "Recently I've been too busy with work, no time to travel"; Interlocutor 2: "You can try going out on the weekend") to minimize response bias.

**Table 1**. The example of the stimuli.

Type	Interlocutor 1 (context)	Interlocutor 2 (comment)				
Irony	我 今天 吃了 一天 的 炸鸡。	你 吃得 真 <b>健康</b> 啊!				
	wo1 jin1tian1 chi1le yi4tian1 de zha2ji1	ni2 chi1de zhen1 jian4kang1 a				
	"I ate fried chicken all day today."	"You eat so healthily!"				
Control	我 今天 吃了 一天 的 沙拉。"	你 吃得 真 <b>健康</b> 啊!"				
	wol jinltianl chille yi4tianl de shallal	"You eat so healthily!"				
	"I ate vegetable salad all day today."					

*Notes:* Bolded text indicates the region of interest.

#### **Procedure**

Questionnaires. Participants' general perceptions of AI chatbots were assessed using a 7-point semantic differential scale (i.e., using bipolar adjectives), adapted from previous research (e.g., Flanagin & Metzger, 2003; Liu & Sundar, 2018; Rheu et al., 2024). Trustworthiness was measured using three bipolar adjective pairs: dishonest-honest, untrustworthy-trustworthy, and unreliable-reliable. Sincerity was evaluated with three additional pairs: insincere-sincere, artificial-genuine, and performed-heartfelt. To capture baseline perceptions, participants in the AI condition completed these measures prior to the EEG experiment. Conversely, participants in the human condition completed the measures post-experiment to maintain the authenticity of their interaction.

**EEG experiment.** A Wizard-of-Oz methodology was employed to create a controlled environment where participants' beliefs about their interlocutor could be manipulated (Kelley, 1984). Participants were led to believe they would read dialogues between two

humans or between an AI companion or a human peer, when in fact, all interactions were pre-programmed and controlled by the experimenter using E-Prime 3.0. Each trial begins with a central fixation cross displayed for 1000 ms, followed by the presentation of Interlocutor 1's context utterance for 5000 ms. A brief 500 ms inter-stimulus interval then preceded a second central fixation cross, presented for 1000 ms. Subsequently, Interlocutor 2's comment was presented word-by-word. Each word appeared for 700 ms, with an inter-word interval of 200 ms. The critical word, an adjective occurring after the second position but not sentence-finally, served as the target stimulus. To ensure engagement and comprehension, questions appeared after 50% of trials in both conditions. These questions probed only the contextual content and did not direct attention toward the ironic interpretation of the comments. All participants achieved accuracy rates above 80% (M = 94.49%, SD = 4.47%).

**Manipulation check for interlocutor.** To validate the experimental manipulation, participants completed a post-experiment survey in which they identified the interlocutors by indicating who had been interacting with Interlocutor 1. Of the 64 participants, 63 correctly identified the interlocutors as either two humans or a human and an AI companion, consistent with their assigned condition (Rheu et al., 2024). One participant in the human condition reported disbelief that the dialogues involved two humans and was therefore excluded from subsequent analyses.

**Post-experiment ratings.** Participants completed a post-task questionnaire assessing the contextual congruence of comments and their underlying communicative motivations. As shown in Figure 1, for each comment by Interlocutor 2, participants first determined whether it matched the context provided by Interlocutor 1. When a mismatch was identified, participants specified the reason by selecting from three options: "Irony", "Politeness", or "Incomprehension" (i.e., Interlocutor 2 failed to understand Interlocutor 1's context). Participants who selected "Irony" subsequently attributed a corresponding motivation by choosing either "Sarcastic" or "Humorous".

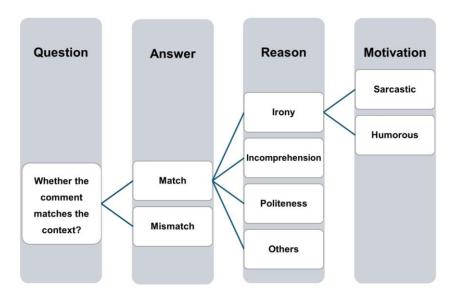


Figure 1. Flowchart of the post-experiment rating process.

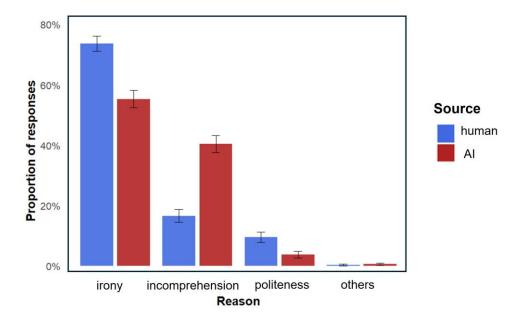
## Data recording and preprocessing

EEG activity was recorded using a 128-channel g.HIamp amplifier with active Ag/AgCl electrodes positioned according to the extended 10-20 system and online-referenced to the left earlobe. Data were sampled at 512 Hz, with electrode impedances maintained below 30 kΩ. Preprocessing was conducted using custom MATLAB scripts and the FieldTrip toolbox (Oostenveld et al., 2011). The continuous EEG was bandpass-filtered between 0.1 and 30 Hz and re-referenced to the averaged earlobes (Luck, 2014). To remove ocular artifacts from the high-density recordings, independent component analysis was performed on the filtered data with dimensionality reduced to 30 components (Luck, 2022; Ghandeharion & Erfanian, 2010; Winkler et al., 2011). The data were segmented into epochs spanning -200 ms to 1000 ms relative to the critical word (i.e., adjective) onset, with baseline correction applied using the -200 ms to 0 ms pre-stimulus interval. Epochs containing voltage deflections exceeding ±150 μV were rejected, resulting in 6.17% trial loss. Five participants were excluded: two for excessive artifact contamination (>30% rejected trials), two for equipment/procedure malfunction, and one for failing the manipulation check, yielding a final sample of 59 participants (25 males; mean age 23.02 years old, range 18-35). Additionally, trials were excluded (3.31%) from EEG analysis based on post-task questionnaire responses: in the irony condition, trials where participants judged Interlocutor 2's comment as contextually congruent were removed; conversely, in the literal condition, trials judged as contextually incongruent were removed.

#### **Results**

#### Behaviorial results

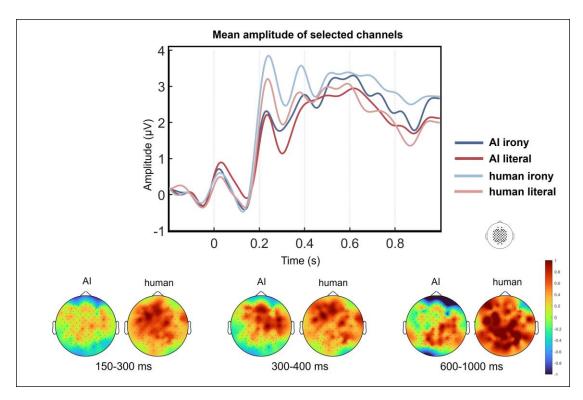
As shown in Figure 2, the majority of ironic stimuli (comments incongruent with context) were correctly identified as ironic. To examine participants' attributions for contextual incongruence, three separate generalized linear mixed-effects models (GLMEs) were fitted with Source as a fixed effect and Participant and Item as random intercepts. For all GLME analyses, we used forward model comparison ( $\alpha = 0.2$ , see Matuschek et al., 2017) to identify the maximal random-effects structure supported by the data. For irony attribution, participants were significantly less likely to attribute AIgenerated incongruent stimuli to irony (N = 634) compared to human-generated stimuli  $(N = 842; \beta = -1.52, t = -2.83, p = .005)$ . For politeness attribution, participants showed a marginally significant tendency to attribute fewer AI-generated incongruent stimuli to politeness (N = 40) compared to human-generated stimuli (N = 102;  $\beta$  = -1.57, t = -1.90, p = .058). For incomprehension attribution, participants were significantly more likely to attribute AI-generated incongruent stimuli to incomprehension (N = 455)compared to human-generated stimuli (N = 177;  $\beta = 2.89$ , t = 4.24, p < .001). Among stimuli attributed to irony, a generalized linear mixed-effects model examined ironic motivation with Source as a fixed effect and Participant and Item as random intercepts. Results showed no significant difference in sarcastic versus humorous motivations between AI and human conditions ( $\beta = 0.09$ , t = 0.244, p = .807).



**Figure 2**. The distribution of contextual mismatch reasons across Source (human vs AI).

## EEG results

Based on visual inspection of the grand average ERP waveforms (Figure 3), we identified three time windows for channel-level amplitude analysis: 150-300 ms (P200), 300-400 ms (P300), and 600-1000 ms (P600) after the critical word onset, aligning with the topography distribution and classic time windows of these components (P200 and P600: Regel & Gunter, 2017; Regel et al., 2010, 2011, 2014; Spotorno et al., 2013; P300: Pritchard, 1981; Ruchkin et al., 1990). For each time window, we selected the same region of interest (ROI) for subsequent amplitude analyses, consisting of 62 central whole-brain sites (see Table S1 for the full list of channels). Rather than collapsing the data within each ROI, we retained individual channel data and included Channel as a random effect in our linear mixed-effects (LME) models, consistent with previous work (Ryskin et al., 2021; Wu & Cai, 2025).



**Figure 3**. Brain potentials elicited by ironic and literal sentences during 150-300 ms, 300-400 ms, and 600-1000 ms after the critical word onset.

Our primary analysis aimed to compare participants' neural responses to irony from AI and human sources. We fit LME models with Type (irony vs. literal) and Source (AI vs. human) as interacting main effects in three time windows, with Participant, Item, and Channel as random effects (see Table 1 for model structures). We used forward model comparison for all LME analyses ( $\alpha=0.2$ , see Matuschek et al., 2017). The results revealed a significant interaction between Type and Source in the 150-300 ms window ( $\beta=-0.39$ , SE=0.06, t=-6.02, p<.001) and the 600-1000 ms window ( $\beta=-0.48$ , SE=0.10, t=-4.81, p<.001). In the 150-300 ms window, separate analyses showed a significant main effect of Type in both the human ( $\beta=0.57$ , SE=0.05, t=11.46, p<.001) and AI conditions ( $\beta=0.18$ , SE=0.34, t=3.73, p<.001). The P200 effect was significantly smaller for AI irony (0.20  $\mu$ V) than for human irony (0.50  $\mu$ V). In the 600-1000 ms window, the main effect of Type was significant in both the human ( $\beta=0.85$ , SE=0.07, t=12.49, p<.001) and AI conditions ( $\beta=0.33$ , SE=0.08, t=4.25, p<.001). The P600 effect was significantly smaller for AI irony (0.34  $\mu$ V) than for human irony (0.78  $\mu$ V).

Additionally, an analysis of the 300-400 ms (P300) window showed no significant interaction between Type and Source ( $\beta$  = 0.11, SE = 0.08, t = 1.30, p = .194). However, we did observe a significant main effect of Type ( $\beta$  = 0.50, SE = 0.04, t = 12.14, p < .001), such that the P300 effect was comparable between the AI and human condition, suggesting this component was elicited by irony regardless of its source.

Table 2. LME models for main ROI analyses.

Main effects	β	SE	t	p
P200 (150-300 ms)				
Intercept	1.85	0.25	7.44	< .001
Type	0.37	0.03	11.20	< .001
Source	-0.84	0.40	-2.07	.043
Type: Source	-0.39	0.06	-6.02	< .001
P300 (300-400 ms)				
Intercept	2.46	0.39	6.33	< .001
Type	0.50	0.04	12.14	< .001
Source	-0.63	0.69	-0.91	.367
Type: Source	0.11	0.08	1.30	.194
P600 (600-1000 ms)				
Intercept	2.43	0.35	6.90	< .001
Type	0.58	0.05	11.03	< .001
Source	-0.02	0.57	-0.04	.968
Type: Source	-0.48	0.10	-4.81	< .001

Model for main amplitude analysis (150-300 ms): Amplitude  $\sim$  Type\* Source + (1 | Participant) + (1 | Item) + (Type + Source + 1 | Channel); Model for main amplitude analysis (300-400 ms): Amplitude  $\sim$  Type\* Source + (1 | Participant) + (1 | Item) + (Source + 1 | Channel); Model for main amplitude analysis (600-1000 ms): Amplitude  $\sim$  Type\* Source + (1 | Participant) + (1 | Item) + (Type + Source + 1 | Channel)

To examine whether neural responses to irony from AI were modulated by participants' perceptions of AI sincerity and trustworthiness, we constructed separate LME models with Type × Sincerity and Type × Trust as interacting fixed effects across three time windows, with Participant, Item, and Channel as random effects (see Table 2 for model structures). The Type × Sincerity interaction was significant in both the 150-300 ms window ( $\beta$  = -0.31, SE = 0.06, t = -6.67, p < .001) and the 600-1000 ms window ( $\beta$  = -0.16, SE = 0.07, t = -2.16, t = -0.031, indicating that P200 and P600

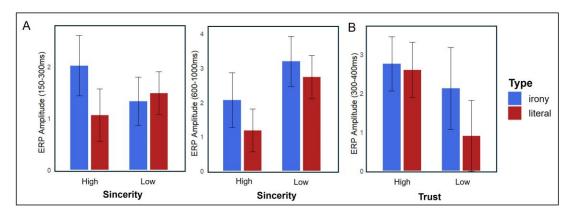
amplitudes to AI irony increased as a function of perceived AI sincerity (Figure 4). Additionally, a significant Type × Trustworthiness interaction emerged in the 300-400 ms window ( $\beta = -0.31$ , SE = 0.06, t = -3.26, p < .001), such that P300 amplitude to AI irony increased with perceived AI trustworthiness (Figure 4).

**Table 3**. LME models for ROI analyses of trust and sincerity in the AI condition.

Main effects	$oldsymbol{eta}$	SE	t	p
Models for trust analyses				
P200 (150-300 ms)				
Intercept	1.43	0.34	4.20	<.001
Type	0.20	0.31	0.63	.531
Trust	0.47	0.32	1.45	.160
Type: Trust	-0.07	0.05	-1.43	.152
P300 (300-400 ms)				
Intercept	2.13	0.59	3.63	<.001
Type	0.55	0.06	9.13	<.001
Trust	0.45	0.61	0.75	.460
Type: Trust	-0.21	0.07	-3.26	<.001
P600 (600-1000 ms)				
Intercept	2.44	0.51	4.78	<.001
Type	0.52	0.52	0.99	.331
Trust	0.45	0.48	0.94	.354
Type: Trust	-0.52	0.57	-0.91	.373
Models for sincerity analyses				
P200 (150-300 ms)				
Intercept	1.46	0.35	4.17	< .001
Type	0.20	0.05	4.26	< .001
Sincerity	-0.05	0.29	-0.16	.875
Type: Sincerity	-0.31	0.05	-6.67	< .001
P300 (300-400 ms)				
Intercept	2.15	0.59	3.64	< .001
Type	2.54	0.66	3.82	< .001
Sincerity	0.03	0.53	0.05	.962
Type : Sincerity	-0.01	0.06	-0.15	.884
P600 (600-1000 ms)				
Intercept	2.46	0.51	4.84	< .001
Туре	0.34	0.44	0.80	.444
Sincerity	-0.39	0.42	-0.92	.365
Type: Sincerity	-0.16	0.07	-2.16	.031

Model for trust analysis (150-300 ms): Amplitude  $\sim$  Type\*Trust + (1 | Participant) + (cType+1 | Item) + (1 | Channel); Model for trust analysis (300-400 ms): Amplitude  $\sim$  Type\*Trust + (1 | Participant) + (1 | Item) + (1 | Channel); Model for trust analysis (600-1000 ms): Amplitude  $\sim$  Type\*Trust + (Type +1 | Participant) + (1 | Item) + (Type +1 | Channel); Model for sincerity analysis (150-300 ms): Amplitude  $\sim$  Type\*Sincerity + (1 | Participant) + (1 | Item) + (1 | Channel);

Model for sincerity analysis (300-400 ms): Amplitude  $\sim$  Type\*Sincerity + (1 | Participant) + (Type +1 | Item) + (1 | Channel); Model for sincerity analysis (600-1000 ms): Amplitude  $\sim$  Type\*Sincerity + (1 | Participant) + (Type + 1 | Item) + (Type + 1 | Channel)



**Figure 4**. A: The modulatory effects of perceived AI sincerity on P200 and P600; B: The modulatory effects of perceived AI trustworthiness on P300.

#### **Discussion**

This study investigated whether human brains process AI-generated irony differently from human-generated irony, exploring the role of *intentional stance* adoption in language comprehension. The behavioral and neural evidence demonstrates that while people can recognize irony from AI, they engage in different cognitive processing compared to human-generated irony, reflecting a limited *intentional stance* toward AI-generated language.

We showed evidence that source attribution alters how people interpret linguistic incongruity. Based on the rating results, irony remains the most common interpretation for contextually incongruent statements in both AI and human conditions. However, compared to the human condition, participants attributed fewer incongruent statements to irony and relatively more to comprehension errors (i.e., interpreting the incongruity as the AI's failure to understand the context) when the source was AI. This cognitive shift suggests that people may not fully engage in mindful anthropomorphism—considering whether AI possesses the mental capacity to craft intentional non-literal meaning (Gray et al., 2007). Although participants still recognized the majority of contextually mismatched statements from AI to irony, the fact that they showed a

relatively higher proportion of mechanistic explanations (i.e., "comprehension errors") compared to the human condition indicates that people selectively withhold the *intentional stance* they naturally apply to human interlocutors. Notably, when statements were identified as ironic, perceived motivation (sarcastic versus humorous) did not differ between sources. This suggests that source attribution affects whether people infer intentionality in the first place, but not how they interpret the social function of that intentionality once recognized.

The brain dynamically adjusts its processing based on the perceived nature of the communicator across three distinct stages indexed by different ERP components. First, the P200 component, which reflects early, domain-specific semantic processing and incongruity detection (Regel et al., 2010), showed reduced amplitude for AI-generated compared to human-generated irony. This suggests the brain initially allocates less attention to semantic incongruity from AI sources, reflecting lower expectations that AI produces intentionally coherent communication. Second, the P300 component, which reflects a domain-general process of integrating new or potentially surprising information into existing understanding (Donchin & Coles, 1988; Ruchkin et al., 1990). The comparable P300 effects between the AI and human conditions indicate that the brain invests similar cognitive effort to update the existing understanding regardless of source. However, late-stage processing diverged markedly. The P600 component, which reflects the effortful cognitive work of reinterpreting apparent errors as intentional irony (Regel & Gunter, 2017; Spotorno et al., 2013), showed significantly reduced amplitude for AI-generated irony. This suggests the brain invests fewer resources in the complex reinterpretation processes needed to recover intentional meaning from AI sources. This neural efficiency aligns with the behavioral pattern: When interpreting AI-generated language, participants displayed a relatively greater tendency to attribute the linguistic incongruity to mechanistic failures (e.g., comprehension errors) and were correspondingly less likely to ascribe it to intentional communication (i.e., true irony), compared to identical human-generated statements. This difference highlights that even when irony remains the dominant overall interpretation, the assumed source shifts how the mind weighs intent versus error.

Together, these three components reveal a dissociation: while domain-general process of updating the existing understanding (P300) remains constant across sources, both domain-specific early semantic processing (P200) and late reanalysis (P600) are modulated by the attribution of the source.

Importantly, adopting the *intentional stance* toward AI is not uniform across individuals but varies with personal beliefs about AI capabilities. Both P200 and P600 amplitudes to AI-generated irony increased among participants who perceived AI as more sincere, suggesting that people who attribute more human-like qualities to AI engage neural mechanisms more similar to those used for human communication. Similarly, P300 amplitude to AI-generated irony increased among participants who perceived AI as more trustworthy, indicating that perceived reliability modulates the updating of existing understanding. These findings demonstrate that while a reduced *intentional stance* represents the people's default processing mode for AI, individual differences in anthropomorphic beliefs and trust shape the neural strategies people employ when comprehending AI-generated language.

These findings connect to broader frameworks in human communication research and human-AI interaction. The differential processing we observed aligns with the principle of interlocutor modeling—the well-established finding that people adjust their comprehension strategies based on characteristics of the speaker (Cai et al., 2021; Wu & Cai, 2024, 2025; Wu et al., 2024, 2025). In our study, this adjustment appears driven by assumptions about differences in mental states and communicative intentions between human and AI sources. Our findings also extend a growing body of research on anthropomorphism in human-AI interaction, which shows that people spontaneously attribute various human-like characteristics to AI, including age (Dou et al., 2021), gender (Powers & Kiesler, 2006), perspective-taking abilities (Loy & Demberg, 2023), and linguistic competence (Dunn & Cai, 2025; Rao et al., 2024). However, our findings provide further evidence for such attribution: people appear to selectively withhold deep mindful anthropomorphism, attributing genuine mental states and communicative intentions to AI. While people treat AI as capable of producing human-like language patterns, the reduced P200 and P600 response indicates they do not fully process AI as

a true intentional agent engaged in deliberate meaning construction.

#### Conclusion

Our findings demonstrate that despite the linguistic capabilities and social agency of modern LLMs, people do not yet fully adopt the *intentional stance* when confronted with AI-generated irony. While people are less likely to attribute linguistic incongruity to a deliberate communicative act and more likely to attribute it to a computational mistake for AI compared to a human source. This is supported by evidence of attenuated domain-specific P200 and P600 effects, which suggests that the brain employs a less effortful and distinct reanalysis strategy for AI-generated incongruity. Notably, these neural responses are modulated by individual perceptions of AI sincerity and trustworthiness, indicating that *intentional stance* adoption is not fixed but depends on people's mental models of the artificial agent. These results show that source attribution is a factor in how the human brain processes social-communicative phenomena. This suggests that for an AI to truly function as a social agent capable of building rapport through mechanisms like humor and irony, it will require more than just linguistic competence; it will necessitate a shift in how humans perceive and attribute genuine intentionality to artificial agents.

#### Reference

- Baron-Cohen, S. (1997). *Mindblindness: An Essay on Autism and Theory of Mind*. Cambridge, MA: MIT Press.
- Braun, H. I., Jackson, D. N., & Wiley, D. E. (2001). Socially desirable responding: The evolution of a construct. In *The role of constructs in psychological and educational measurement* (pp. 61-84). Routledge.
- Cai, Z., Duan, X., Haslett, D., Wang, S., & Pickering, M. (2024, August). Do large language models resemble humans in language use?. In *Proceedings of the Workshop on Cognitive Modeling and Computational Linguistics* (pp. 37-56). https://aclanthology.org/2024.cmcl-1.4/
- Cai, Z. G., Sun, Z., & Zhao, N. (2021). Interlocutor modelling in lexical alignment: The

- role of linguistic competence. *Journal of Memory and Language*, *121*, 104278. https://doi.org/10.1016/j.jml.2021.104278
- Casu, M., Triscari, S., Battiato, S., Guarnera, L., & Caponnetto, P. (2024). AI chatbots for mental health: a scoping review of effectiveness, feasibility, and applications. *Applied Sciences*, 14(13), 5889. https://doi.org/10.3390/app14135889
- Chen, X., Li, D., & Wang, X. (2022). Uighur college students' irony comprehension in Chinese. *International Journal of Bilingualism*, 26(4), 450-475. https://doi.org/10.1177/13670069211056128
- Dennett, D. C. (1987). The Intentional Stance. Cambridge, MA: MIT Press
- Donchin, E., & Coles, M. G. (1988). Is the P300 component a manifestation of context updating?. *Behavioral and Brain Sciences*, 11(3), 357-374.
- Dou, X., Wu, C. F., Lin, K. C., Gan, S., & Tseng, T. M. (2021). Effects of different types of social robot voices on affective evaluations in different application fields. *International Journal of Social Robotics*, 13, 615-628. https://doi.org/10.1007/s12369-020-00654-9
- Dunn, M. S., & Cai, Z. G. (2025). Linguistic alignment of redundancy usage in humanhuman and human-computer interaction. *Applied Psycholinguistics*, 46, e22. https://doi.org/10.1017/S0142716425100118
- Epley, N., Waytz, A., & Cacioppo, J. T. (2007). On seeing human: a three-factor theory of anthropomorphism. *Psychological Review*, *114*(4), 864. https://doi.org/10.1037/0033-295X.114.4.864
- Flanagin, A. J., & Metzger, M. J. (2003). The perceived credibility of personal Web page information as influenced by the sex of the source. *Computers in Human Behavior*, 19(6), 683-701. https://doi.org/10.1016/S0747-5632(03)00021-9
- García-Méndez, S., de Arriba-Pérez, F., & Somoza-López, M. D. C. (2025). A review on the use of large language models as virtual tutors. *Science & Education*, *34*(2), 877-892. https://doi.org/10.1007/s11191-024-00530-2
- Ghandeharion, H., & Erfanian, A. (2010). A fully automatic ocular artifact suppression from EEG data using higher order statistics: Improved performance by wavelet

- analysis. *Medical Engineering & Physics*, *32*(7), 720-729. https://doi.org/10.1016/j.medengphy.2010.04.010
- Go, E., & Sundar, S. S. (2019). Humanizing chatbots: The effects of visual, identity and conversational cues on humanness perceptions. *Computers in Human Behavior*, 97, 304–316. https://doi.org/10.1016/j.chb.2019.01.020
- Gray, H. M., Gray, K., & Wegner, D. M. (2007). Dimensions of mind perception. *Science*, *315*(5812), 619-619. https://doi.org/10.1126/science.1134475
- Kelley, J. F. (1984). An iterative design methodology for user-friendly natural language office information applications. *ACM Transactions on Information Systems (TOIS)*, 2(1), 26–41.
- Krach, S., Hegel, F., Wrede, B., Sagerer, G., Binkofski, F., & Kircher, T. (2008). Can machines think? Interaction and perspective taking with robots investigated via fMRI. *PloS one*, *3*(7), e2597. https://doi.org/10.1371/journal.pone.0002597
- Leslie, A. M. (1994). Pretending and believing: issues in the theory of ToM. *Cognition* 50, 211–238.
- Loy, J. E., & Demberg, V. (2023). Perspective taking reflects beliefs about partner sophistication: Modern computer partners versus basic computer and human partners. *Cognitive Science*, 47(12), e13385. https://doi.org/10.1111/cogs.13385
- Luck, S. J. (2014). An introduction to the ERP technique, second edition. In *MIT Press*. MIT Press. https://books.google.com.hk/books?id=y4-uAwAAQBAJ
- Luck, S. J. (2022). Applied Event-Related Potential Data Analysis. https://socialsci.libretexts.org/Bookshelves/Psychology/Book%3A\_Applied\_EventRelated Potential Data Analysis (Luck)
- Maples, B., Cerit, M., Vishwanath, A., & Pea, R. (2024). Loneliness and suicide mitigation for students using GPT3-enabled chatbots. *npj Mental Health Research*, 3(1), 4. https://doi.org/10.1038/s44184-023-00047-6
- Matuschek, H., Kliegl, R., Vasishth, S., Baayen, H., & Bates, D. (2017). Balancing Type I error and power in linear mixed models. *Journal of Memory and Language*, 94, 305–315. https://doi.org/10.1016/j.jml.2017.01.001

- Nass, C., & Moon, Y. (2000). Machines and mindlessness: Social responses to computers. *Journal of Social Issues*, 56(1), 81-103. https://doi.org/10.1111/0022-4537.00153
- Oostenveld, R., Fries, P., Maris, E., & Schoffelen, J. M. (2011). FieldTrip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. *Computational Intelligence and Neuroscience*, 2011. https://doi.org/10.1155/2011/156869
- Powers, A., & Kiesler, S. (2006). The advisor robot: tracing people's mental model from a robot's physical attributes. In *Proceedings of the 1st ACM SIGCHI/SIGART conference on Human-robot interaction* (pp. 218-225). https://doi.org/10.1145/1121241.1121280
- Pritchard, W. S. (1981). Psychophysiology of P300. *Psychological bulletin*, 89(3), 506. https://doi.org/10.1037/0033-2909.89.3.506
- Rao, X., Wu, H., & Cai, Z. G. (2024, October 8). Comprehending semantic and syntactic anomalies in LLM- versus human-generated texts: An ERP study. https://doi.org/10.31234/osf.io/kvbg2
- Rao, X., Wu, H., & Cai, Z. G. (2025). A funny companion: Distinct neural responses to perceived AI-versus human-generated humor. *arXiv preprint arXiv:2509.10847*. https://doi.org/10.48550/arXiv.2509.10847
- Regel, S., Coulson, S., & Gunter, T. C. (2010). The communicative style of a speaker can affect language comprehension? ERP evidence from the comprehension of irony. *Brain Research*, *1311*, 121-135. https://doi.org/10.1016/j.brainres.2009.10.077
- Regel, S., & Gunter, T. C. (2017). Don't get me wrong: ERP evidence from cueing communicative intentions. *Frontiers in Psychology*, 8, 1465. https://doi.org/10.3389/fpsyg.2017.01465
- Regel, S., Gunter, T. C., & Friederici, A. D. (2011). Isn't it ironic? An electrophysiological exploration of figurative language processing. *Journal of Cognitive Neuroscience*, 23(2), 277-293. https://doi.org/10.1162/jocn.2010.21411
- Regel, S., Meyer, L., & Gunter, T. C. (2014). Distinguishing neurocognitive processes

- reflected by P600 effects: Evidence from ERPs and neural oscillations. *PloS one*, 9(5), e96840. https://doi.org/10.1371/journal.pone.0096840
- Rheu, M., Dai, Y., Meng, J., & Peng, W. (2024). When a chatbot disappoints you: Expectancy violation in human-chatbot interaction in a social support context. Communication Research, 51(7), 782-814. https://doi.org/10.1177/00936502231221669
- Ritschel, H., Aslan, I., Sedlbauer, D., & André, E. (2019, May). Irony Man: Augmenting a Social Robot with the Ability to Use Irony in Multimodal Communication with Humans. In *Proceedings of the 18th International Conference on Autonomous Agents and MultiAgent Systems* (pp. 86-94).
- Ruchkin, D. S., Johnson Jr, R., Canoune, H. L., Ritter, W., & Hammer, M. (1990).
  Multiple sources of P3b associated with different types of information. *Psychophysiology*, 27(2), 157-176. https://doi.org/10.1111/j.1469-8986.1990.tb00367.x
- Ryskin, R., Stearns, L., Bergen, L., Eddy, M., Fedorenko, E., & Gibson, E. (2021). An ERP index of real-time error correction within a noisy-channel framework of human communication. *Neuropsychologia*, *158*, 107855. https://doi.org/10.1016/j.neuropsychologia.2021.107855
- Sperber, D., & Wilson, D. (1981). Irony and the use-mention distinction. *Philosophy*, 3(1), 143-184.
- Spotorno, N., Cheylus, A., Van Der Henst, J.-B., and Noveck, I. A. (2013). What's behind a P600? integration operations during irony processing. PLOS ONE 8:e66839. doi: 10.1371/journal.pone.0066839
- Thellman, S., De Graaf, M., & Ziemke, T. (2022). Mental state attribution to robots: A systematic review of conceptions, methods, and findings. *ACM Transactions on Human-Robot Interaction (THRI)*, 11(4), 1-51. https://doi.org/10.1145/3526112
- Utsumi, A., Watanabe, Y., & Wakayama, Y. (2013). Do people understand irony from computers?. In *Proceedings of the Annual Meeting of the Cognitive Science Society* (Vol. 35, No. 35).
- Weng, X., Jiang, X., & Liao, Q. (2023). Using information of relationship closeness in

- the comprehension of Chinese ironic criticism: Evidence from behavioral experiments. *Journal of Pragmatics*, 215, 55-69. https://doi.org/10.1016/j.pragma.2023.07.005
- Winkler, I., Haufe, S., & Tangermann, M. (2011). Automatic Classification of Artifactual ICA-Components for Artifact Removal in EEG Signals. Behavioral and Brain Functions, 7(1), 30. https://doi.org/10.1186/1744-9081-7-30
- Wu, H., & Cai, Z. G. (2024). Speaker effects in spoken language comprehension. *arXiv* preprint arXiv:2412.07238.
- Wu, H., & Cai, Z. G. (2025). When a Man Says He Is Pregnant: Event-related Potential Evidence for a Rational Account of Speaker-contextualized Language Comprehension. *Journal of Cognitive Neuroscience*. https://doi.org/10.1162/JOCN.a.102
- Wu, H., Duan, X., & Cai, Z. G. (2024). Speaker Demographics Modulate Listeners' Neural Correlates of Spoken Word Processing. *Journal of Cognitive Neuroscience*, 36(10), 2208-2226. https://doi.org/10.1162/jocn a 02225
- Wu, H., Rao, X., & Cai, Z. G. (2025). Probabilistic adaptation of language comprehension for individual speakers: Evidence from neural oscillations. *Social Cognitive and Affective Neuroscience*, nsaf085. https://doi.org/10.1093/scan/nsaf085