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Abstract

According to the Uniform Information Density (UID) hypothesis, speakers prefer utterances in which information is spread evenly across the linguistic signal. Despite abundant empirical evidence for UID across multiple levels of linguistic representations, the reasons for why UID effects arise are less well understood. Here we explore a listener-oriented hypothesis that a communicative need to facilitate listener comprehension contributes to UID effects. To assess this possibility, we test whether and how information distribution patterns in naturalistic dialogues are shaped by individual differences in speakers' socio-cognitive traits. We hypothesize that if UID effects stem at least partly from speakers taking listeners' needs into account, then speakers with greater socio-cognitive abilities should exhibit stronger UID effects. Using corpus data, we show that UID is modulated by the speaker's ability to infer others' mental states, supporting the listener-oriented hypothesis of UID. We discuss the implications of the current work for refining theories of UID and, more broadly, for incorporating social cognition into accounts of the cognitive mechanisms underlying language processing.

Keywords: Uniform Information Density; naturalistic language production; social cognition; individual differences

Introduction

A longstanding line of research in linguistics and cognitive science has proposed that human language is organized according to general principles governing the flow of information. Under these accounts, language users are hypothesized to optimize the rate of information transmission during communication, resulting in systematic regularities such as Entropy Rate Constancy (ERC; Genzel & Charniak, 2002, 2003) and Uniform Information Density (UID; Jaeger, 2010; Levy & Jaeger, 2007). For example, UID predicts that speakers tend to structure their utterances to distribute information as evenly as possible across the linguistic signal to ensure robust transmission of information while maintaining efficient use of the communication channel.

Following Shannon's (1948) information theory, the information density of a linguistic unit (e.g., morpheme, word) given its context, $I(u)$ is defined as in (1), where $P(u|context)$ denotes the contextual probability of u. This is also commonly referred to as *surprisal* (Hale, 2001; Levy, 2008).

(1) $I(u) \propto -\log P(u \mid context)$

Research supporting the UID hypothesis in language production spans multiple linguistic levels, including phonetics (Aylett & Turk, 2004), lexical choice (Mahowald et al., 2013), syntax (Jaeger, 2010), and discourse (Asr & Demberg, 2015). For example, past research across many different languages has consistently demonstrated that when a word or phoneme is more predictable in context, it is typically produced with a shorter duration and exhibits reduced phonological and phonetic detail (Aylett & Turk, 2004; Cohen Priva, 2015, among others). At the lexical level, Mahowald et al. (2013) found that speakers are more likely to use shortened forms of words (e.g., math instead of mathematics) in more predictive contexts. Similarly, at the syntactic level, studies have shown that optional syntactic markers, such as that in English complement clauses (e.g., *I think (that) the weather is very nice*; Hao & Kaiser, 2025; Jaeger, 2010; Rabinovich, 2024) and object relative clauses (e.g., the groceries (that) they brought home; Levy & Jaeger, 2007), are more frequently omitted when the upcoming syntactic structure is highly predictable. The relationship between information density and syntactic reduction also extends cross-linguistically, such as in subject doubling in French (Liang, Amsili, Burnett, & Demberg, 2024) and optional indefinite articles in German (Lemke, Horch, & Reich, 2017).

However, despite extensive evidence for UID across multiple levels of linguistic representation, much less is known about why UID emerges. Prior studies have convincingly demonstrated that speakers tend to distribute information relatively uniformly, but the cognitive and communicative mechanisms behind this pattern remain underspecified.

Most theoretical accounts derive UID effects from the assumption that linguistic communication proceeds through a noisy channel with limited bandwidth (e.g., Genzel & Charniak, 2002; Jaeger, 2006, 2010; Jaeger and Buz, 2018; Levy and Jaeger, 2007; Temperley and Gildea, 2015; cf. Shannon, 1948). Within this framework, maintaining uniform information density is probably optimal for maximizing successful information transmission. A natural interpretation of this noisy-channel assumption is that the "channel" refers to communication between interlocutors,

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which motivates a listener-oriented view of UID. Under this interpretation, speakers regulate information density to avoid sudden spikes that could overload the listener, thereby facilitating comprehension. This perspective aligns UID with broader audience-design phenomena (e.g., Jaeger, 2010; Jaeger & Buz, 2018), in which speakers adjust their linguistic choices based on interlocutors' knowledge, cognitive state, or processing constraints (Brown & Dell, 1987; Clark & Murphy, 1982; Lockridge & Brennan, 2002; Ahn & Brown-Schmidt, 2020).

If UID indeed reflects speakers' sensitivity to listeners' processing needs, then variation in speakers' trait-level social-cognitive abilities should shape the degree to which they exhibit UID. In the current work, we test this hypothesis by examining Conversation: A Naturalistic Dataset of Online Recordings (CANDOR; Reece et al., 2023), which contains naturalistic dyadic conversations from 1,456 speakers, together with detailed survey data that measures socio-cognitive traits and broader personality dimensions.

Related Work

Before reporting our analysis, we review research on the relationship between information distribution and communicative needs, and on individual differences in language processing, as our work builds on both domains.

UID and Communicative Goals

To investigate the communicative nature of UID, prior work has examined it within the framework of audience design. In the domain of phonetic reduction, some studies have found that it is sensitive to audience design (Galati & Brennan, 2010; Pate & Goldwater, 2015). For example, Pate and Goldwater (2015) compared the effects of phonetic reduction between infant-directed and adult-directed speech, as well as between speech to visible and invisible listeners, and found that speakers adjust the strength of phonetic reduction based on listener characteristics and visual cues. In recent work, Ouyang and Kaiser (2021) found that the degree of emphasis with which a speaker produces corrective prosody is modulated by the addressee's knowledge state. However, other laboratory-based studies failed to elicit listener-specific audience design effects (e.g., Arnold, Kahn, & Pancani, 2012; Bard & Aylett, 2004; Kahn & Arnold, 2013).

At the lexical level, there is a more robust relationship between reduction and audience design. For example, it has been suggested that speakers' preferences among pronouns, names, and full NPs reflect audience design considerations, and that speakers are capable of taking their interlocutors' perspective and knowledge state into account when choosing referential expressions (Arnold, 2008; Arnold, 2010; Vogels, Howcroft, Tourtouri, & Demberg, 2019). Tal, Grossman, and Arnon (2024) additionally show that speakers adjust levels of lexical redundancy based on listeners' language proficiency. However, see also Arnold and Griffin (2007), who argue that speakers may produce more descriptive referring expressions due to their own increased cognitive load or attentional resources rather than audience design.

Finally, at the syntactic level, to the best of our knowledge no work has directly investigated whether audience design modulates UID-based syntactic reduction. Some studies have examined optional syntactic reduction as a mechanism for ambiguity avoidance, which can be viewed as a general form of audience design. However, this prediction has rarely been supported by empirical findings (Arnold, Wasow, Asudeh, & Alrenga, 2004; Ferreira, 2008; Ferreira & Dell, 2000; Roland, Elman, & Ferreira, 2006; Wasow & Arnold, 2003). Similarly, Morgan and Ferreira (2022) investigated resumptive pronouns as a potential outcome of audience design at the syntactic level but found no supporting evidence.

In sum, most prior work that probed the communicative nature of UID focused audience design and has yielded mixed results. Moreover, this work has focused on phonetic and lexical reduction or redundancy.

In our work, rather than examining how speakers adjust their production for variation among listeners, we focus on the other side of the coin—variation among speakers themselves.

Individual Differences in Language Processing

While the majority of psycholinguistic studies have focused on group-level effects, substantial evidence suggests that individual variation in certain cognitive and social traits can modulate processing. For example, numerous studies have examined effects of working memory and executive control in language comprehension and production (e.g., Daneman & Green, 1986; King & Just, 1991; Huettig & Janse, 2015; Newman, Malaia, Seo, & Cheng, 2012; Nicenboim, Logačev, Gattei, & Vasishth, 2016; Roberts & Gibson, 2002; Veenstra, Antoniou, Katsos, & Kissine, 2018). What's most relevant for our work are studies investigating individual differences in socio-cognitive traits, including pragmatic and communicative skills and theory-of-mind abilities.

In the domain of pragmatic inferences, Nieuwland, Ditman and Kuperberg (2010) examined the impact of underinformative versus informative scalar statements (e.g., "Some people have lungs/pets, and…") on the N400 ERP component, an electrophysiological marker of semantic processing. They found that only participants with higher pragmatic skills (measured by the Communication Subscale of the Autism-Spectrum Quotient (AQ) test (Baron-Cohen, Wheelwright, Skinner, Martin, & Clubley, 2001)) exhibited a larger N400 response to underinformative statements. This suggests that sensitivity to pragmatic violations varies based on individual differences in communicative ability. Similar effects have been found in other studies, suggesting that individuals with stronger pragmatic and communicative skills are more likely to derive non-literal inferences (e.g., Katsos & Bishop, 2011; Feeney & Bonnefon, 2012; Yang, Minai, and Fiorentino, 2018; Yu, 2010; see also Ryzhova, Mayn & Demberg, 2023, who found that higher AQ scores are associated with less pragmatic inferences). It is generally assumed by these authors that individuals with greater socio-cognitive skills may be better at adopting the interlocutor's perspective or infer communicative intent, leading to more pragmatic or non-literal interpretations of utterances.

Other research has also investigated how pragmatic reasoning is affected by individual differences in Theory of Mind (ToM) abilities (e.g., Bendtz, Ericsson, Schneider, Borg, Bašnáková, & Uddén, 2022; Cummings et al., 2024; Rasgado-Toledo, Lizcano-Cortés, Olalde-Mathieu, & Licea-Haquet, 2021; Trott & Bergen, 2020), as measured by the Reading the Mind in the Eyes Test (RMET; Baron-Cohen, Jolliffe, Mortimore, & Robertson, 1997), and personality (Taguchi, 2014). For example, Yu, Abrego-Collier, and Sonderegger (2013) examined alignment in speech production using a comprehensive set of questionnaires assessing a diverse range of cognitive and social skills and personality traits, including AQ and the Big Five Inventory (BFI; John, Donahue, & Kentle, 1991; Soto & John, 2017). Their findings suggest that both social and personality factors play a role in modulating phonetic alignment.

Building on these prior studies, we investigate effects of individual differences in socio-cognitive traits on information distribution patterns in naturalistic conversations.

Current Work

The current work examines the hypothesis that UID arises from speakers' communicative need to accommodate listeners, focusing on how trait-level individual differences influence this process. We test whether individual differences in socio-cognitive abilities modulate UID in dyadic conversations. We hypothesize that individuals with stronger socio-pragmatic skills will better adhere to UID.

Our work makes several contributions. First, to the best of our knowledge, this work is the first to test if the extent to which speakers exhibit UID, i.e., how smoothly information is distributed in their language production, is shaped by individual differences, thereby providing novel evidence of the social-cognitive bases of UID. Second, it brings an individual-differences perspective to naturalistic language production, leveraging corpus-based conversational data rather than controlled laboratory tasks. In doing so, we also develop a reusable analytical pipeline that brings together conversational language modeling, information-theoretic analysis, and socio-cognitive individual differences. Finally, it integrates a broad battery of measures from social psychology to test how social-cognitive traits interface with psycholinguistic processes. By bridging social psychology and psycholinguistics, this study offers a more comprehensive account of linguistic cognition and its relation to social cognition.

Data

We use the CANDOR corpus (Reece et al., 2023), a dataset of 1,656 dyadic conversations between pairs of strangers over Zoom. The corpus is publicly accessible by request and includes audio recordings and survey metadata for each participant. In total, 1,456 unique speakers are represented, spanning diverse gender identities, ethnic backgrounds, educational levels, and age groups. Conversations are spontaneous and unscripted, with an average duration of 31.3 minutes (SD = 7.96; minimum length = 20 min).

For the present analysis, we used corpus transcripts, which contain roughly 8 million words. Transcripts were segmented using the Cliffhanger algorithm, which clusters utterances into conversational units based on terminal punctuation while incorporating backchannels into surrounding units. In addition, we will leverage the corpus's survey data, which includes an extensive set of cognitive, social, and communicative ability measures.

Information Density and Information Uniformity

The two key components of our analysis are (i) the information density of each word in the corpus and (ii) the overall information uniformity of a given conversation. We discuss each of these in more depth below.

First, note that the current work differs from prior work that examines UID at configurational levels, which compares the effects of information density on a specific linguistic phenomenon (such as *that*-reduction and phonetic reduction). By contrast, we are interested in how to measure the overall information uniformity of texts and utterances.

To do so, we follow the operationalization of information uniformity in Meister, Pimentel, Haller, Jäger, Cotterell, and Levy (2021), where the information uniformity U of a text with n words is defined in Equation (2) as the inverse of the mean squared deviation (MSD) of each word's information density from the mean information density $\bar{I}$. This measure captures the extent to which information is evenly distributed throughout the text. A higher U value indicates a more uniform distribution of information, better aligning with UID. In contrast, a lower value of U reflects greater variability in word-level information distributions.

(2) $U = 1/((1 / \mathrm{n}) \times [(\mathrm{I}(w_1) - \bar{I})^2 + (\mathrm{I}(w_2) - \bar{I})^2 + \ldots + (\mathrm{I}(w_\mathrm{n}) - \bar{I})^2])$

To estimate per-word information density, i.e., $\mathrm{I}(w_\mathrm{n})$, we used the autoregressive language model GPT-2 (Radford et al., 2019). Information density is defined in (1) and restated in (3) for word-level units. For each word, we estimated its conditional probability $P(w_n \mid \text{context})$, with the context consisting of all preceding words in the current turn as well as in previous turns of the conversation.

(3) $I(w) \propto -\log P(w \mid context)$

A Note on Mean Information Density. One question concerns the level at which mean information density $\bar{I}$ should be computed (e.g., sentence, turn, or whole conversation). Meister et al. (2021) found that operationalizing information uniformity at the full-language level yielded the highest psycholinguistic predictive accuracy. Theoretically, this also aligns with the original UID proposal (e.g., Levy & Jaeger, 2007), which posits that UID emerges as a byproduct of language users optimizing their use of a communication channel. In this work, we adopt this global view and compute $\bar{I}$ as the mean information density across all utterances of a speaker in the same conversation.

Selecting Individual Difference Measures

In this section, we review the psychological surveys completed by participants in the CANDOR corpus that assess socio-cognitive abilities.

Autism-Spectrum Quotient (AQ). The AQ is a self-report questionnaire designed to assess the extent to which an individual exhibits traits commonly linked to Autism Spectrum Conditions (ASC), developed by Baron-Cohen et al. (2001). The test comprises 50 items categorized into five subscales: social skills (SS), communication (CM), attention to detail (AD), attention switching (AS), and imagination (IM). Responses are recorded using a 4-point Likert scale. Each subscale has a scoring range from 10 to 40. The total AQ score is the sum of all items. Higher scores reflect stronger associations with ASC-related traits, such as reduced social skills, difficulty shifting attention, enhanced focus on detail and patterns, impaired communication abilities, and lower imaginative capacity. AQ has also been widely used to assess socio-communicative skills of neurotypical population (e.g., Eriksson, 2013; Nieuwland et al., 2010; Velikonja, Fett, & Velthorst, 2019; Yu et al., 2013).

Interpersonal Reactivity Index (IRI). The IRI (Davis, 1980) is a widely used self-report questionnaire designed to measure different dimensions of empathy. It includes 28 items on four subscales that assess distinct aspects of empathic responding: Empathic Concern (EC), Perspective Taking (PT), Fantasy (FS), and Personal Distress (PD). EC measures emotional empathy (feelings of compassion and concern for others), PT measures cognitive empathy (the ability to adopt another person's point of view), FS assesses the tendency to imaginatively place oneself in fictional situations, and PD captures self-oriented distress in response to others' suffering. Each subscale consists of seven items rated on a 5-point Likert scale, where higher scores typically indicate greater emotional or cognitive empathy, except for PD. Similar to AQ, the IRI has been used to assess neurotypical populations (e.g., Gupta, Basu, & Thakurta, 2022; Kanske, Schönfelder, & Wessa, 2013).

Reading the Mind in the Eyes Test (RMET). The RMET (developed by Baron-Cohen et al., 1997) is a psychological measure designed to assess Theory of Mind, specifically the ability to infer emotions and mental states from subtle facial expressions. It is considered a key tool in cognitive and social psychology for evaluating mental state attribution, an essential component of social cognition. The test consists of 36 black-and-white photographs of human eyes, depicting various emotional and mental states. Participants choose which of four mental-state labels (e.g., *thoughtful, worried, playful, skeptical*) best describes each image. Higher scores indicate stronger ability to infer mental states, suggesting higher cognitive empathy and social perceptiveness; lower scores may reflect difficulties in social cognition. Again, this measure has also been applied to non-neurodivergent populations (e.g., Bendtz et al., 2022; Carroll, Montrose, & Burke, 2021; Dodell-Feder, Ressler, Germine, 2020).

Big Five Inventory (BFI). The Big Five Inventory (BFI) assesses five major personality dimensions: Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism (John et al., 1991; Soto & John, 2017). These dimensions reflect broad, stable personality traits that influence cognition, behavior, and social interaction. The BFI consists of 44 items rated on a 5-point Likert scale. Openness reflects curiosity, creativity, and preference for novelty; Conscientiousness reflects self-discipline and organization; Extraversion reflects sociability and assertiveness; Agreeableness reflects prosocial tendencies such as trust and empathy; and Neuroticism reflects emotional instability and anxiety. The BFI is frequently used in personality, cognitive, and social psychology to investigate how personality traits shape behavior, decision-making, and interpersonal communication (Byrne, Silasi-Mansat, & Worthy, 2015; Kuntze, Van der Molen, & Born, 2016; Paunonen, 2003; Sims, 2017). Traits such as Agreeableness and Openness have been linked to enhanced social cognition and perspective-taking, whereas Neuroticism has been associated with difficulties in social inference and emotion recognition (e.g., Austin, 2005; Nettle & Liddle, 2008).

To summarize, we have reviewed four surveys that assess socio-cognitive traits, including pragmatic and communicative skills (AQ), theory-of-mind and empathic abilities (RMET, IRI), and broader personality dimensions (BFI). Furthermore, while only some BFI dimensions, i.e., Agreeableness, and Openness, are theoretically linked to socio-cognitive behavior (e.g., Nettle & Liddle, 2008), we analyzed all five BFI traits for completeness and to provide a comprehensive baseline characterization of personality differences. This approach allows us to situate socio-cognitive traits within the broader landscape of individual variation and to assess whether UID effects are selectively driven by social-cognitive factors rather than personality traits more generally.

Assessing Multicollinearity. However, some of these (sub)scales may be correlated. For example, the Agreeableness, Openness, and Neuroticism dimensions of the BFI may correlate with the SS and CM subscales of the AQ, the EC and PT subscales of the IRI, as well as RMET scores. It is also reasonable to hypothesize that RMET may correlate with EC and PT. While some studies have not found such correlations (Muller et al., 2010), Jansen, Overgaauw, and de Bruijn (2020) reported a correlation between the FS subscale of the IRI and RMET scores. To assess potential multicollinearity among predictors, we conducted pairwise correlation analyses and examined variance inflation factors (VIF). These diagnostics ensured that predictors could be included simultaneously in the linear mixed-effects models.

Statistical Analysis

We used mixed-effects linear regression models (Bates, Mächler, Bolker, & Walker, 2015) to examine the relationship between information uniformity and socio-cognitive measures. The independent variables consist of (sub)scales of the AQ, IRI, RMET, and BFI (all normalized), and the dependent variable is conversation-level uniformity. Because each conversation involves two speakers and some speakers participated in multiple conversations, we included speaker ID and conversation ID as random intercepts.

Because the majority of the participants completed the BFI but only a small subset completed the remaining measures, two models were fit. The **first model** included all participants who completed the BFI (1,431 unique speakers; 3,287 data points). The **second model** included only participants who also completed the AQ, RMET, and IRI measures (175 participants; 592 data points). The formulas for the two models are reported in (4) and (5), respectively.

(4) **BFI (model 1):** Uniformity ~ Openness + Conscientiousness + Extraversion + Agreeableness + Neuroticism + (1 | speaker) + (1 | conversation)

(5) **Other measures (model 2):** Uniformity ~ AQ-CM + AQ-SS + RMET + IRI-PT + IRI-EC + (1 | speaker) + (1 | conversation)

Results

Before discussing results of the models, we report the correlation between the survey measures. The correlation heatmap between the independent variables for both models are shown in Figure 1 and Figure 2, respectively. As can be seen in the plots, no predictors exhibited strong pairwise associations. We also computed VIFs for both models, and all VIF values were well below common thresholds (i.e., VIF < 5). As a matter of fact, all VIF values in our models are < 2), indicating no problematic multicollinearity.

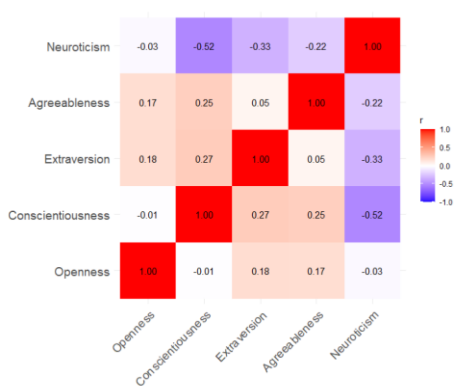

Figure 1: Correlation heatmap BFI (model 1).

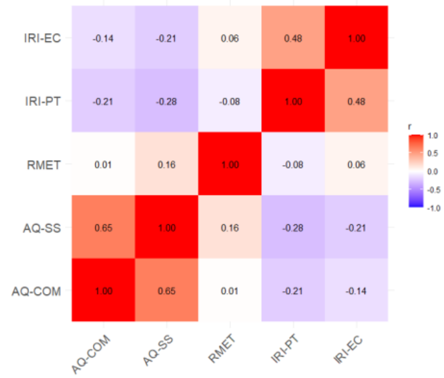

Figure 2: Correlation heatmap AQ, RMET, IRI (model 2).

Results of the first analysis (model 1) examining **the effects of BFI traits** on information uniformity are reported in Table 1. Agreeableness was the only significant predictor (β=0.061, SE=0.024, t =2.593, p<0.01): higher agreeableness scores were associated with greater information uniformity. No other BFI traits showed significant effects.

Table 1: Effects of the BFI traits.

Predictor	β	SE	t	p
Openness	−0.013	0.023	−0.584	0.560
Conscientiousness	0.036	0.026	1.384	0.167
Extraversion	−0.011	0.024	−0.482	0.630
Agreeableness	**0.061**	**0.024**	**2.593**	**<0.01****
Neuroticism	0.033	0.027	1.238	0.216

Results of the second analysis (model 2) examining **the effects of AQ subscales, RMET, and IRI subscales** on information uniformity are reported in Table 2. We did not find significant effects of the AQ subscales or the IRI subscales. However, RMET scores were positively associated with information uniformity: individuals with higher RMET scores exhibited greater information uniformity in their language production.

Table 2: Effects of AQ, RMET, and IRI

Predictor	β	SE	t	p
AQ-CM	0.019	0.071	0.272	0.786
AQ-SS	0.030	0.073	0.417	0.678
RMET	**0.134**	**0.053**	**2.510**	**<0.05***
IRI-PT	−0.010	0.065	−0.162	0.872
IRI-EC	−0.098	0.062	−1.576	0.117

Discussion

In this study, we examined how general regularities in information smoothing during language use relate to individual differences in socio-cognitive traits, focusing on the principle of UID. We hypothesized that speakers may prefer to produce utterances that adhere to UID in order to facilitate listener comprehension. To test this possibility, we examined whether trait-level individual differences in socio-cognitive abilities modulate information uniformity in naturalistic conversational data. We analyzed the effects of the BFI factors, the RMET, AQ subscales, and IRI subscales.

We first consider the effects of the BFI. As we noted earlier, not all of these personality dimensions are theoretically linked to socio-cognitive factors relevant for communicative adaptation. It is therefore not surprising that only a subset of the traits showed significant relationships with information uniformity. Among the five predictors, only Agreeableness emerged as a significant positive predictor. This aligns with the interpretation that agreeableness captures tendencies toward cooperation, empathy, and accommodating others' needs, traits that are most closely connected to socio-cognitive sensitivity during interaction. The remaining traits did not show reliable effects, suggesting that UID is selectively modulated by socio-cognitive traits rather than by personality traits more broadly.

The second model included two AQ subscales, RMET scores, and two IRI subscales, which more directly target socio-cognitive abilities relevant for communication, perspective taking and listener adaptation. However, surprisingly, only the RMET predicted information uniformity. We think this pattern arises from these instruments indexing different components of social cognition. The AQ subscales primarily capture socio-communicative challenges, such as difficulties with conversational pragmatics, interpreting implied meanings, and navigating social conventions, but do not directly assess mental state attribution. The IRI subscales measure cognitive and affective empathy via self-report, and while IRI-PT is conceptually related to mentalizing, prior work has shown mixed empirical associations between empathy and theory of mind (e.g., Keysers & Gazzola, 2007).

In contrast, the RMET assesses the ability to infer others' mental states from subtle facial cues and is widely treated as a behavioral measure of theory of mind. Because UID likely depends on the extent to which speakers track and anticipate listeners' informational needs, it may be more sensitive to this kind of cue-based, context-sensitive mentalizing than to socio-communicative skills or self-reported empathy.

Consistent with this interpretation, higher RMET scores, indicating stronger mental state inference abilities, were associated with greater adherence to UID, suggesting that UID may reflect a listener-oriented form of communicative adaptation grounded in theory-of-mind processes.

Intriguingly, this pattern is consistent with our BFI results where Agreeableness, the dimension most closely tied to interpersonal sensitivity and socio-pragmatic accommodation, showed significant effects, whereas the other traits did not. Together, these findings suggest that information uniformity may depend on listener-oriented processes grounded in mentalizing and interpersonal accommodation rather than on broader personality factors, communicative skills, or self-reported empathic tendencies.

Conclusion

We investigated whether trait-level individual differences relevant to socio-cognitive skills influence how speakers distribute information during linguistic production. The theoretical motivation for this work stems from the listener-oriented hypothesis that speakers adhere to the UID principle to facilitate comprehension for their interlocutors. Unlike prior work, which has primarily examined how speakers adapt to different interlocutors, we ask whether stable individual traits affect *how much* speakers adhere to UID. To our knowledge, this is the first study to probe individual differences in UID and, more broadly, the first to examine the effects of trait-level socio-cognitive differences on language production in naturalistic dialogue.

Our findings carry theoretical and methodological implications. First, they refine accounts of UID by showing that information uniformity in spontaneous production is not a static or production-internal phenomenon but is modulated by individual differences in socio-cognitive traits. In particular, we identify RMET scores and Agreeableness from the BFI as predictors of greater uniformity, pinpointing which traits matter for UID rather than simply establishing that UID varies across speakers.

Second, our work highlights a scalable methodological approach for studying individual differences in naturalistic language use: we combine corpus-based conversational data and automated linguistic metrics with validated psychological instruments, offering a template for future work that aims to investigate trait-induced variation in language processing. This approach helps bridge psycholinguistics and individual differences research, illustrating how naturalistic corpora can be leveraged to test cognitive hypotheses at scale.

Finally, our findings contribute to ongoing efforts to develop a more integrated theory of linguistic cognition. While language processing has long been viewed primarily as a cognitive enterprise supported by systems such as working memory, executive control, and attentional regulation, along with verbal knowledge and semantic memory (e.g., Fedorenko, 2014; Just & Carpenter, 1992; Ullman, 2004), growing research highlights the importance of individual variability beyond traditional cognitive skills (e.g., Kidd, Donnelly, & Christiansen, 2018; Yu & Zellou, 2019). Although individual differences in verbal ability and executive resources are well-studied, personality and socio-cognitive traits remain comparatively neglected, and their theoretical relationship to linguistic processing is often implicit rather than explicit. By showing that trait-level differences in theory of mind and interpersonal sensitivity shape online language production, we provide evidence that social-cognitive traits modulate core processing mechanisms. This aligns with emerging theoretical perspectives that treat linguistic behavior as arising from the interaction of cognitive, linguistic, and socio-cognitive systems (e.g., Li & Huang, 2024). By linking UID to individual socio-cognitive dispositions, our study advances this integrative approach and highlights new directions for research on language processing.

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