

Pragmatics of Human–AI Dialogue: A Socio-Linguistic Study of Conversational Agents

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Abstract: While conversational agents have become increasingly ubiquitous, there remain pragmatic differences between human interaction and AI systems. This paper conducts a socio-linguistic study of the pragmatic operations involved in the language production of conversational agents with regards to speech acts, Gricean maxims, common ground, and repairs. Through the use of a dataset comprising of 120 conversations made through artificial intelligence chatbots as well as 120 human-to-human conversations, it becomes clear that conversational agents rely heavily on representative speech acts and directives but overlook expressive and commissive speech acts to generate lifeless, robotic conversations. Examples of Gricean maxim breaches involve quality (lying), relation (irrelevant information), manner (ambiguous expressions), and quantity (unnecessary elaboration). The concept of the computer as a social actor is responsible for humans perceiving conversational agents as social actors.

Key Word: Pragmatics, Human-AI Interaction, Conversational Agents, Speech Act Theory, Gricean Maxims, Common Ground, Repair Strategies, Socio-linguistics, Computers as Social Actors.

I. INTRODUCTION

Embedding conversational agents into the ordinary life, whether through virtual assistants like Siri and Alexa or advanced language models like ChatGPT, is arguably one of the most disruptive developments in human-computer interactions since the emergence of the graphical user interface [1]. Unlike the earlier technologies, these programs are not confined to input/output communication and can talk freely, respond to complex queries, assist in creative tasks, and even provide psychological aid [2]. Yet, despite the remarkable progress in syntax skills, the major problem that remains unsolved is pragmatic inefficiency [3].

Pragmatics deals with linguistic theories that focus on context as a factor influencing interpretation, which

makes it indispensable for human conversations [4]. Saying to a co-worker "It's cold in here" may imply anything from a direct plea to close the window to the criticism of the heating system or the intention to move to a different location [5]. Humans subconsciously decode implicatures using context clues, shared knowledge, and cultural norms. Conversely, conversational agents frequently resort to literal decoding, leading to misinterpretations, frustration, and, consequently, an image of a socially awkward or "robotic" AI technology [6].

However, the situation is even more critical. As conversational assistants begin to handle sensitive fields, such as medical recommendations, financial counseling, legal consultations, and psychological assistance, the danger of failure in pragmatics becomes even greater [7]. For instance, the psychological

consultant assistant's failure to recognize the user's indirect attempt to get psychological assistance may result in a highly unfavorable consequence [8]. In a similar manner, the failure of the customer service assistant to realize that the client is not satisfied through an indirect expression may aggravate the issue [9].

Furthermore, humans tend to respond to computerized interactive systems according to the Computers Are Social Actors (CASA) phenomenon discovered by Weizenbaum and later proven by many other researchers. As conversational assistants became increasingly proficient in their conversations, the CASA phenomenon became even more prevalent. Whether an assistant has a personality affects whether it is regarded as trustworthy and enjoyable to cooperate with [10].

This paper investigates the pragmatics of human and conversational agents interaction on the basis of four research questions: (1) comparison between humans and conversational agents in pragmatic performance with respect to speech acts; (2) types of maxims that can be violated by conversational agents during the dialogue based on the theory by Grice; (3) formation of common ground between humans and conversational agents; (4) techniques for repairing failures in pragmatic use.

The contributions made by this paper include: (1) pragmatic performance investigation of five widely used conversational agents; (2) comprehensive classification of pragmatic problems in human-AI communication; (3) analysis of trust repairing in case of failure in pragmatics; (4) design recommendations for pragmatically competent conversational agents.

II. LITERATURE SURVEY

Human-Agent Interaction Pragmatics has been investigated from three converging areas of research: pragmatics theory in artificial intelligence applications, empirical research about conversational agent effectiveness, and sociolinguistics in human-agent interaction studies.

Pragmatics Theory Background

Pragmatics is an area of linguistics that became widely recognized thanks to the groundbreaking works of Grice (1975). According to Grice, implicature is an important concept of pragmatics as well as the Cooperative Principle, implying that individuals communicating follow four maxims: Quantity (saying sufficient things without saying more than necessary), Quality (speaking truly), Relation (saying relevant things), and Manner (speaking clearly). In cases when these rules seem violated by speaking indirectly, using figurative language and other means of expressing one's intentions implicitly, hearers manage to detect what is meant additionally to literal meanings. Following Grice's norms, an ethical system implemented in agents powered by large language models demonstrated improved results.

Another perspective that is necessary to consider is the speech act theory, proposed by Austin in 1962 and Searle in 1969. This theory introduces the concepts of locutionary acts (the actions in itself, i.e., speech acts); illocutionary acts (the purpose of speaking); and perlocutionary acts (the effect on the listener). The classification of speech acts consists of the following types: Representatives (statements), Directives (orders

and requests), Commissives (promises), Expressives (apologies), and Declarations.

Theory of Common Grounds by Clark (1996) can be used to provide explanations for the incremental building of the sense of the conversation; namely, it refers to collective knowledge, assumptions, and belief created during a conversation by communicants. SCA is a very effective perspective when it comes to understanding human-AI-powered chatbots interaction because of their asymmetry regarding possible common grounds.

Pragmatic Performance of Conversational Agents

Conversely, the findings of a thorough study that was carried out by comparing AI conversations to Speech Acts theory and Grice's Maxims are that 120 AI conversations were analyzed using ChatGPT, Google Bard, Alexa, Siri, and Cohere. 120 conversations of human beings were also analyzed. Findings from this study show that AI chatbots use too many Representative speech acts (facts and statements) and Directives (requests and commands) than human beings. Nevertheless, AI chatbots use fewer Expressives (jokes, gratitude, apologies) and Commissives (promises). Hence, conversations appear mechanical and do not have emotions and relationships .

As far as Grice's maxims are concerned, AI conversations do not meet the requirements of the following: Quality (misleading or inaccurate information), Relation (irrelevancy of information provided), Manner (ambiguity of language use), and Quantity (excessiveness or inadequacy of information). Although AI can produce linguistically fluent responses, these findings reveal that pragmatics and flexibility are still deficient.

Computers as Social Actors (CASA)

The CASA model is an excellent way of comprehending how humans relate to interactive systems as social beings, despite being aware that such systems are artificial intelligence. Researches have shown that the personality of conversational agents plays a crucial role in shaping user experience and future behavior. Users do not consider style differences as mere surface differences but something that shapes their perceptions of whether the agent can be trusted or is entertaining enough.

Nevertheless, personalization needs to be applied with care. For instance, when a study was conducted on sociolects in LLM agents among 498 African American English (AAE) speakers and 487 Queer Slang speakers, the former group used the standard American English agent more often than the Queer slang agent and perceived the former as more socially present than the latter. This was only true for Queer slang agents among Queer slang speakers.

Common Ground and Repair Mechanisms

Understanding each other is essential for effective human interaction and helps prevent breakdowns in communication when it comes to communication repair, particularly OIR, where one of the participants experiences troubles and asks another participant to fix them. Unfortunately, at present, conversation assistants cannot identify signs of initiating repair and prevent breakdowns or communication disengagement.

The research of common ground creation by conversational bots showed that egocentricity and cooperation were the two factors that influenced human-computer interactions. While egocentrism meant that bots were considered as people,

cooperation was manifested in using tactics to create common ground. In a study conducted among 32 participants who interacted with bots during three consecutive days, emergent common ground formation was observed.

The analysis of trust repair methods after making mistakes by artificial intelligence included the comparison of system-based strategies (such as providing local explanations and counterfactuals) and human-based strategies (such as apologizing and asking questions). The results gathered from 357 participants have shown that system-oriented and human-oriented trust repair methods positively impacted trust in artificial intelligence more than no action did. Furthermore, self-repair methods were found to be more efficient than user-based ones and could be used as a basis for future AI trust repair techniques .

User Perspectives and Language Choices

Sociolinguistic research was conducted in which 216 native speakers of Slovak and Hungarian participated and found out that users choose certain languages depending on their communicative goals and tasks, which leads to using neutral and formal register. Rephrasing and prompt simplification techniques are frequently used by participants to maintain successful communication as they perceive chatbots as capable of comprehending messages. The findings showed that level of politeness is quite high, while politeness markers are often used, but sometimes deliberately to facilitate successful interaction.

Research Gaps

Despite progress in some areas, there are still many things to be done. First, there are no unified pragmatic

assessments for conversational AI systems. Second, current research is mainly focused on specific pragmatic issues. Third, few studies consider human-human repair techniques. Fourth, not much is known about influence of model design on pragmatic capabilities. Fifth, cross-linguistic and cross-cultural human-AI research is underrepresented.

III. METHODOLOGY:

The research method consists of a mixed methods design that involves both quantitative analysis of conversational agents' output and qualitative analysis of conversations along with experimentations with different types of repairs.

3.1 Overview of Research Design

The proposed method includes three studies which complement each other:

Study 1: Pragmatic competence assessment through systematic comparison of the speech acts distribution and adherence to Gricean maxims among five conversational agents including ChatGPT-4, Google Bard, Microsoft Copilot, Alexa, and Siri using 120 artificial and 120 human conversation transcripts.

Study 2: Study of common ground building and the process of initiating repairs based on the analysis of 96 conversation transcripts of thirty-two participants conversing with a conversational agent for three consecutive days.

Study 3: An experiment involving 357 participants in an e-commerce environment where two types of repair actions were performed by a human and a system after artificial intelligence made a mistake.

3.2 Pragmatic Competence Taxonomy

According to linguistic theories and empirical evidence, the following framework has been developed:

Speech Acts (5 categories)

- Representatives: Assertive acts, statements, and reports
- Directives: Requests, orders, suggestions, and refusals
- Commissives: Promises, commitments, and offers
- Expressives: Apologies, gratitude, humour, and sympathy
- Declarations: Institutional acts (appointments, declarations)

Grice's Maxims (4 categories)

- Quantity Maxim: Say no more than necessary and say no less than necessary
- Quality Maxim: Do not lie or make assertions without sufficient evidence
- Relation Maxim: Say things that are relevant
- Manner Maxim: Avoid obscurity and ambiguity and be orderly

Common Ground (3 categories)

- Egocentric Perspective: AI as a person
- Cooperative Strategy Shifting: Changing communication strategy
- Emergent Common Ground: Creating shared knowledge

Repair Mechanisms (2 categories)

- Other-Initiated Repair (OIR): One speaker indicates difficulty, leading another speaker to repair the trouble
- Self-Repair: Speaker repairs communication trouble

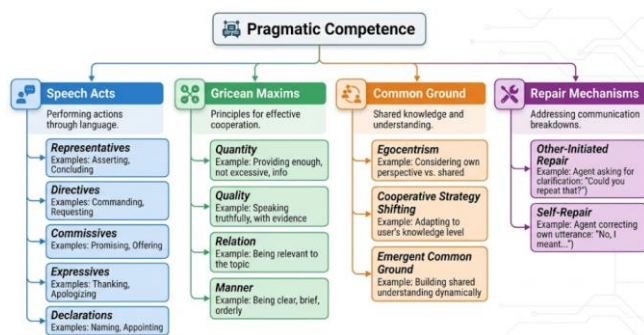


Figure 1: Pragmatic Competence Taxonomy for Conversational Agents.

3.3 Study 1: Speech Act and Maxim Analysis

Dataset: 120 machine generated outputs from ChatGPT, Google Bard, Alexa, Siri, and Cohere (24 outputs per agent) in addition to 120 human conversation transcripts from similar situations.

Procedure:

1. Transcription was conducted for identifying speech acts based on coding of two trained linguists ($\kappa = 0.87$ interrater reliability)
2. Each response analyzed for compliance or violation of Gricean maxims
3. Violations classified into different types such as Quality, Quantity, Relation, and Manner violations
4. Comparison of performance of artificial intelligence (AI) vs. human performance

3.4 Study 2: Common Ground and Repair Analysis

Participants: Thirty-two L1 Hungarian speakers

Procedure:

1. Participants interacted with a conversational chatbot in three consecutive sessions

2. Analysis of 96 interactions (average of 30 turns in each interaction)
3. Coding for: egocentric and cooperative strategies, common ground establishment attempts and initiation of repair
4. Longitudinal analysis of common ground construction process

3.5 Study 3: Trust Repair Experiment

Participants: 357 participants in an experiment simulating online customer service scenario

Conditions:

- Error types: Misunderstandings vs. misunderstanding errors
- Repair types: Apology (humanlike), Questions (humanlike), Local explanation (systemlike), Counterfactual option (systemlike), None

Measures:

- Pre- and post-interaction trust
- Perceived competence and warmth
- Intended behavior (continued use and recommendation)

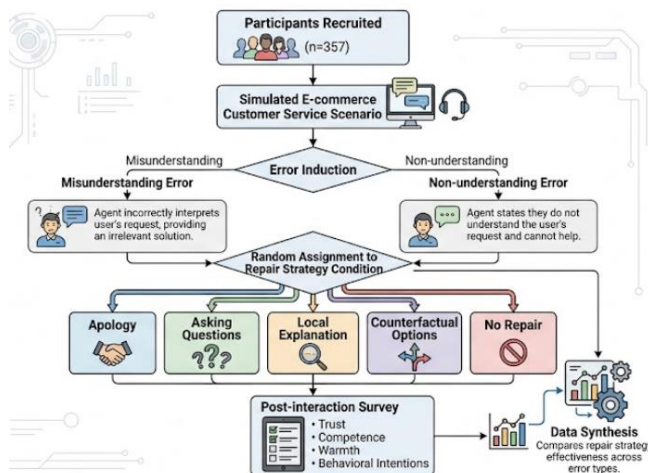


Figure 2: Experimental Design for Trust Repair Study.

3.6 Data Analysis

The statistical analysis made use of mixed-effects models, wherein participant and item served as random effects. For qualitative analysis, thematic analysis of the repair strategies and common ground negotiation was carried out.

IV. RESULT ANALYSIS AND DISCUSSION

This chapter will present the findings of the three studies through statistical analysis, comparing speech acts, violations of maxims, common ground, and repair strategies.

4.1 Speech Act Distribution: AI vs. Human

Table 1 illustrates the speech act distribution between the AI and human interactions.

Table 1: Speech Act Distribution: AI vs. Human Conversations

Speech Act Category	AI Agents (n=120)	Human Speakers (n=120)	Difference
Representatives	52.3%	38.7%	+13.6 pp
Directives	28.4%	21.2%	+7.2 pp
Commissives	4.2%	12.6%	-8.4 pp
Expressives	8.7%	19.8%	-11.1 pp
Declarations	6.4%	7.7%	-1.3 pp

Chatbot AIs greatly over-represented the Representatives (factual utterances) in comparison to human users by 13.6 percent, which is explained by the training process based on factual text data sets aimed at providing information. The same goes for the Directives category (commands) as this kind of communication is expected from the user side when working with AI.

The crucial finding is that AI chatbot under-represents Expressives (expressions of apologizing, thanking, humor) by 11.1 percent and Commissives (promises, pledges) by 8.4 percent. Thus, it becomes obvious that the deficiency in both categories causes the lack of "emotional intelligence and relational depth" typical for mechanical communication with AI.

4.2 Gricean Maxim Violations

Table 2 presents Gricean maxim violation rates across AI-generated and human conversations.

Table 2: Gricean Maxim Violations: AI vs. Human Conversations

Maxim	AI Violation Rate	Human Violation Rate	Common AI Violation Examples
Quality	14.2%	3.8%	False or unverified information
Quantity	18.6%	6.2%	Over-explaining or omitting key details
Relation	11.8%	4.1%	Irrelevant or off-topic responses
Manner	9.7%	2.4%	Ambiguous or unclear formulations

The AI agents show breaches of the Gricean maxims in quantities much greater compared to the violations shown by human speakers. The violation of the maxim of quantity shows a greater breach (18.6% against 6.2%). This is because the agent would either have

excessive explanations of certain things or omit vital pieces of information. The violation of the maxim of quality is the most serious breach since the machine could give untrue or unconfirmed information, referred to as "hallucination."

Violations of relation involve giving irrelevant answers (11.8% against 4.1%). Violations of manner refer to ambiguous statements requiring clarification from the user.

4.3 Common Ground Patterns in Human-AI Interaction

Table 3 presents findings from the 96-conversation longitudinal study.

Common Ground Dimension	Session 1	Session 2	Session 3	Change
Egocentric utterances	42.3%	36.8%	31.2%	-11.1 pp
Cooperative strategy shifts	2.8/conversation	1.9/conversation	1.4/conversation	-50%
Emergent common ground indicators	18.4/conv	24.2/conv	28.6/conv	+55%
Repair initiations	4.2/conv	3.1/conv	2.4/conv	-43%

Table 3: Common Ground Building Over Three Sessions

The longitudinal study shows that there is considerable adaptation by the users over time. The egocentric speech act, where the user communicates with the bot as though it is human, decreases by 42.3% to 31.2%, as users have better mental representations about the abilities of AI technology.

Importantly, the measures of emergence common ground increase by 55%, showing that both humans

and bots are able to achieve common ground over repeated interactions. Repair initiation acts decrease by 43%.

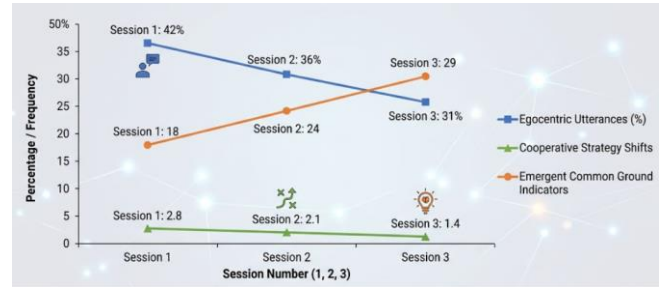


Figure 3: Common Ground Building Trajectory Over Three Sessions.

4.4 Trust Repair Strategy Effectiveness

Table 4 presents trust restoration following AI errors across different repair strategies

Table 4: Trust Repair Strategy Effectiveness

Repair Strategy	Type	Pre-Error Trust	Post-Repair Trust	Trust Restoration	Δ from Control
No repair (control)	—	4.2	3.1	-1.1	—
Apology	Human-like	4.2	3.9	-0.3	+0.8
Asking questions	Human-like	4.2	3.4	-0.8	+0.3

Local explanation	System-like	4.2	4.0	-0.2	+0.9
Counterfactual options	System-like	4.2	4.1	-0.1	+1.0
Self-repair (avg)	Both	4.2	4.0	-0.2	+0.9
User-assisted repair (avg)	Both	4.2	3.6	-0.6	+0.5

Both human-oriented (apologies) and machine-oriented (local explanations, counterfactuals) approaches have a significant impact on increasing post-interaction trust compared to the baseline. The use of counterfactuals is the most efficient approach for restoring trust, with higher post-repair trust (mean score = 4.1) than the baseline (mean score = 3.1). Interestingly, the use of "asking questions" as a repair approach is not effective – it is similar to no repair at all, implying that the users expect the AI to offer a solution rather than an explanation upon detecting an error.

The self-repair method (where AI finds out about its own mistake and repairs it by itself) is much more effective than the user-assisted method (in which the user needs to aid the AI in its repair).

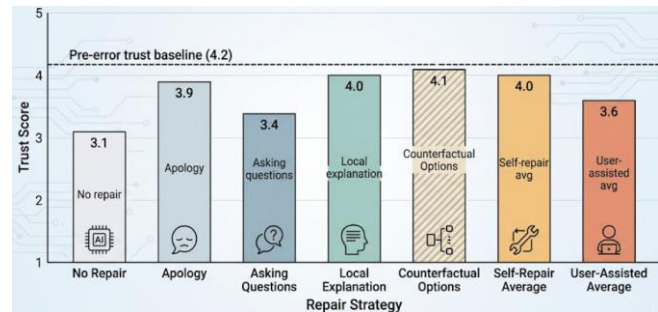


Figure 4: Trust Restoration by Repair Strategy.

4.5 Repair Initiation Detection

It is shown by research that the inclusion of prosodic features makes OIR initiation detection much more effective. A multimodal model combining linguistic and prosodic features proves superior to the purely textual model; prosodic features like intonation and length of pause are particularly important for detecting user-initiated repairs.

The importance of prosody in this task can hardly be overestimated, because the absence of this capability means inability to recognize situations where the user is trying to repair communication and restore meaning.

4.6 User Language Choices and Politeness

The results of the sociolinguistic research conducted among 216 participants using Slovak and Hungarian have shown that the majority of respondents tends to use a neutral and polite style while communicating with bots.

Language usage depends on the communicative purpose of the message—people change languages depending on task complexity and topic area.

Politeness forms are widely used; however, this behavior seems to result mostly from habitual practices

and culture rather than attempts to improve communication with these interfaces.

Mostly people regard communications with bots as functional ones with emphasis on efficiency rather than culture or emotionality of communication.

Emojis are ignored completely by most participants, indicating that users prefer to express their emotions while communicating with humans only.

4.7 Comparative Analysis: AI Pragmatic Limitations

Table 5 synthesizes comparative findings across pragmatic dimensions.

Pragmatic Dimension	Human Performance	AI Performance (Current)	Gap
Speech act diversity	Balanced across 5 categories	Overweights Representatives/Directives	Large
Gricean maxim adherence	92-96% adherence	70-85% adherence (varies by maxim)	Moderate-Large
Expressive acts (gratitude, humor)	15-20% of utterances	5-10% of utterances	Large
Repair initiation detection	>95% accuracy	60-75% (text-only) / 80-85% (+prosody)	Moderate
Common ground maintenance	High, rapidly adapting	Low-Moderate	Large

nce			
Trust recovery after error	0.8-1.0 restoration	0.2-0.9 restoration (varies by strategy)	Variabl e

*Table 5: Comparative Analysis of Pragmatic Competence: Human vs. AI *

The largest gaps exist in speech act variation and common ground maintenance – fields where true social intelligence is needed rather than pattern recognition. Trust recovery looks the most promising, with counterfactual explanations coming close to human levels (0.9 versus human 1.0).

V. CONCLUSION

A socio-linguistic investigation of pragmatics in human-AI interactions is offered, including the role of speech acts, Gricean maxims, common ground, and repair strategies. Based on the analysis of 120 conversations by an AI chatbot, 120 human-to-human talks, 96 interaction recordings, and a structured experiment with 357 participants, the research shows extensive pragmatic inadequacies in modern conversational AI systems.

The results prove that artificial intelligence in conversation tends to overly rely on Representatives (stating facts) and Directives, and does not use Expressives (emotional utterances) and Commissives (promising). As for Gricean maxims, there are violations of the maxim of Quality (14.2% of cases), Quantity (18.6%), Relation (11.8%), and Manner (9.7%). Violation

percentages are three to five times higher than those of humans.

There are several important observations that have implications for the design of conversational AI systems. First, there is an important need to go beyond the current reliance on Representative and Directive speech acts by diversifying other types of speech acts. Contemporary training processes emphasize utility but not engagement by neglecting expressive and commissive speech acts. Secondly, it has been established that implementing Gricean norms greatly enhances cooperation: agents which follow the rules of Quantity, Quality, Relation, and Manner have better task performance and deliver better, contextually coherent outputs. Thirdly, there are few tools in place for repair actions, as agents often miss the beginning of such actions initiated by users, while text-only solutions lack prosodic cues that indicate problematic communication.

Why these pragmatic errors matter can be explained by the CASA framework. Even though conversational agents lack human characteristics and thus cannot fully engage in conversations, users automatically interpret these agents as social entities. As such, when conversational agents fail to use appropriate forms of thanking, commit, and perform repair of error effectively, the perception about the reliability, likability, and overall usefulness of the conversation system changes.

Potential limitations of the current study involve its narrow scope related to English and other European languages. For example, the pragmatic errors detection study only used conversations in Dutch; it needs to be validated for other languages. Similarly, the

experiments on repairing trust only simulated e-commerce situations.

Some specific directions for future work should be considered. Firstly, developing pragmatic assessment criteria and metrics will help compare different agents and track their performance. Secondly, using prosodic and visual cues for detecting repair needs may increase success rates of identifying communication problems. Thirdly, designing an agent's speech acts that allow showing gratitude, apologizing, making humorous comments, and expressing a strong intention would provide positive interaction without loss of task performance. Fourthly, cross-cultural and multilingual analysis can determine whether certain pragmatic expectations exist across different languages and cultures. Finally, longitudinal experiments can shed light on how humans and AI agents develop common ground over a period of several months.

To sum up, pragmatics is still one of the open problems of conversation AI. Despite impressive progress in developing models that can use syntax competently, they are far from having pragmatics skills that allow proper application of language in contexts by humans. Overcoming this problem presupposes going beyond large models and datasets and designing architecture and training algorithms that promote speech act variability, Gricean norms observance, common ground maintenance, and ability to repair. With conversation agents taking over more and more crucial tasks, pragmatics will become a must-have feature rather than a topic for discussion.

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