"I'm Not Sure, But...": Examining the Impact of Large Language Models' Uncertainty Expression on User Reliance and Trust

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ABSTRACT

Widely deployed large language models (LLMs) can produce convincing yet incorrect outputs, potentially misleading users who may rely on them as if they were correct. To reduce such overreliance, there have been calls for LLMs to communicate their uncertainty to end users. However, there has been little empirical work examining how users perceive and act upon LLMs' expressions of uncertainty. We explore this question through a large-scale, pre-registered, human-subject experiment (N=404) in which participants answer medical questions with or without access to responses from a fictional LLM-infused search engine. Using both behavioral and self-reported measures, we examine how different natural language expressions of uncertainty impact participants' reliance, trust, and overall task performance. We find that first-person expressions (e.g., "*I'm not sure, but...*") decrease participants' confidence in the system and tendency to agree with the system's answers, while increasing participants' accuracy. An exploratory analysis suggests that this increase can be attributed to reduced (but not fully eliminated) overreliance on incorrect answers. While we observe similar effects for uncertainty expressed from a general perspective (e.g., "*It's not clear, but...*"), these effects are weaker and not statistically significant. Our findings suggest that using natural language expressions of uncertainty may be an effective approach for reducing overreliance on LLMs, but that the precise language used matters. This highlights the importance of user testing before deploying LLMs at scale.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**; • **Computing methodologies → Artificial intelligence**.

KEYWORDS

Large language models, Uncertainty expression, Trust in AI, Overreliance, Human-AI interaction

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1 INTRODUCTION

Large language models (LLMs) are transforming our daily lives. Today millions of people already incorporate LLMs into everyday tasks like searching for information [56, 66], writing [38, 105], and programming [3, 70, 79]. However, the use of LLMs raises significant risks [11, 14, 99]. Notably, like all models, LLMs are imperfect. They are widely recognized to produce outputs that are fluent and plausible, yet ultimately wrong [41, 42, 52]. This can lead to disastrous outcomes through *overreliance* [19, 25, 76, 92], when people take actions based on incorrect outputs. This concern garnered much public attention in 2023 when a lawyer included fake judicial opinions generated by ChatGPT in a legal brief presented in court [100]. Such risks have been at the forefront of regulators' minds when drafting new frameworks for governing AI including the Draft AI Act in the European Union [75] and the NIST AI Risk Management Framework in the United States [87]. In fact, Article 14 of the Draft EU AI Act explicitly requires developing and evaluating approaches to prevent overreliance on AI systems. However, overreliance is notoriously difficult to mitigate, as many mitigations, such as explanations, are found to be ineffective or even can backfire to increase overreliance [7, 76, 77, 97, 108].

As one approach to reduce overreliance, the research community has called for LLMs and LLM-infused applications to express the uncertainty of outputs to end users [6, 50, 51, 67, 91, 110]. The idea of conveying AI uncertainty is not new; in AI-assisted decision-making settings, communicating (un)certainty has been shown to support trust calibration [108], increase vigilance [78], and improve task performance [7]. But because of their open-ended outputs, wide-ranging use cases and user bases, and shifting public perception, LLMs raise new questions around how to

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both estimate and express uncertainty [50, 91]. For estimation, "default" approaches are often found to be overconfident [26, 67, 103], and a new line of work has emerged on improving their calibration [4, 26, 31, 47, 51, 53, 67, 88, 110]. For expression, LLMs open up a new design space; instead of presenting uncertainty numerically or visually, LLMs can present natural language expressions of uncertainty — for instance, hedging phrases like "*I'm not sure, but...*" — embedded in their outputs. Still, there is little understanding about how to effectively express uncertainty in natural language to end users.

To deploy LLMs responsibly, it is necessary to understand how users react to uncertainty expression before implementing approaches at scale since it may have unintended negative consequences — potentially even increasing overreliance if it causes the system to appear more trustworthy than it is. Best practices for uncertainty expression will play a critical role in ensuring that requirements like those in the Draft EU AI Act serve their intended purpose. To that end, we study how people perceive and act upon an LLM's expression of uncertainty when seeking medical information using a fictional LLM-infused search engine. We choose to study this setting because search (unlike, for example, creative writing) is an application in which the correctness of responses is fundamental — especially for potentially high-stakes medical queries — making overreliance a serious concern. Additionally, LLM-infused search engines are already used by millions of people.[1]

We choose to focus on natural language expressions for several reasons. First, LLM-infused search engines already include hedging language [50, 56, 67]. Second, social science research shows that, in human communication, expressing (un)certainty through natural language is often preferred and perceived as more intuitive than numerical expressions [33, 54, 96, 102, 111]. Third, this allows uncertainty to be expressed seamlessly within the natural language interactions of LLM-infused applications, rather than on the side or in onboarding materials [21, 68, 73] that users might overlook.

Taking inspiration from the uncertainty communication literature — both in the context of AI systems and person-to-person [72, 106] — we also explore the impact of the perspective used to express the uncertainty, comparing expressions in the first person (e.g., "*I'm not sure, but...*") with expressions from a general perspective (e.g., "*It's not clear, but...*").

Concretely, we conduct a large-scale, pre-registered, human-subject experiment (N=404) in which participants answer medical questions with or without access to responses from a fictional LLM-infused search engine, referred to as "AI System A." We randomly vary whether participants have access to the system's responses as well as the presence (present/not present) and perspective (first-person/general) of uncertainty expressed in these responses. We measure the impact of these experimental conditions on factors including participants' accuracy, the amount of time they take, their reliance on the system's responses versus other sources of information, and their self-reported trust in the system.

We find that participants who are shown first-person expressions of uncertainty are less confident in the system's answers, agree with the system's answers less often, and submit more correct answers compared with participants who see no expression of uncertainty. An exploratory analysis suggests that the increased accuracy can be attributed to reduced (but not fully eliminated) overreliance on the system's incorrect answers. While we observe similar effects for uncertainty expressed from a general perspective, these effects are weaker and not statistically significant. These results suggest that expressing uncertainty through natural language can be an effective way to reduce overreliance and (over)trust in LLM-infused search engines. Still, we advocate for teams building and deploying LLMs to evaluate approaches to mitigate overreliance, including language choices, carefully with end users before release and for policymakers to embrace diverse and flexible approaches.

2 RELATED WORK

2.1 Uncertainty Expression

Uncertainty expression has been studied extensively both in the context of AI and in the context of human communication. Estimates of uncertainty can be expressed in different ways, including numerically (e.g., "*a probability of 0.2*"), visually (e.g., displaying error bars), and through natural language (e.g., "*with high uncertainty...*"). While numerical expressions and visualizations allow for high precision, they are notoriously difficult for people to understand and are often misinterpreted, even by experts [9, 40, 43, 86]. In contrast, while less precise, natural language expressions of uncertainty are often perceived to be more intuitive and favored by people [33, 54, 96, 102, 111]. Because of this, and since LLMs already produce natural language outputs, we focus on natural language expressions in our study.

Different forms of natural language uncertainty expression have been studied by researchers in disciplines ranging from psychology [30, 95, 101] and human-computer interaction [5, 37, 89] to communication [59] and marketing [36, 72]. Our study design builds on this literature. Most notably, in the context of marketing, Oba and Berger [72] found that different types of hedges — a form of uncertainty expression — have different levels of persuasion, with the most persuasive being those that suggest a high likelihood of occurrence (e.g., "*probably*" as opposed to "*possibly*") and those that take a personal, first-person perspective (e.g., "*I feel like...*") as opposed to a general perspective (e.g., "*It feels like...*"). Indeed, taking a first-person perspective is often found to increase the engagement in the persuasion literature [24]. This motivated our exploration of the effect of AI uncertainty expressions taking a first-person or general perspective, though we explore the *negative* persuasive effect (i.e., deterring overreliance) of expressing uncertainty.

Many methods have been proposed for estimating and communicating uncertainty in AI systems [13]. Most relevant, several studies have shown that communicating uncertainty can reduce overreliance. In the context of house valuation, Prabhudesai et al. [78] found that visualizing a system's uncertainty using quantile dot plots forced participants to slow down and think analytically. In the context of sentiment classification and question answering, Bansal et al. [7] found that displaying a system's numerical confidence improved participants' task performance.

A few studies have looked specifically at natural language expressions of uncertainty in AI systems. They have been studied in the chatbot literature as a design strategy to prevent user frustration from conversational breakdowns [5, 37]. Radensky et al. [80]

[1]In March 2023, Microsoft reported Copilot in Bing served 45 million chats in the first month of its public preview [66]. Perplexity AI reported its service had reached 2 million monthly active visitors in four months [2, 85].

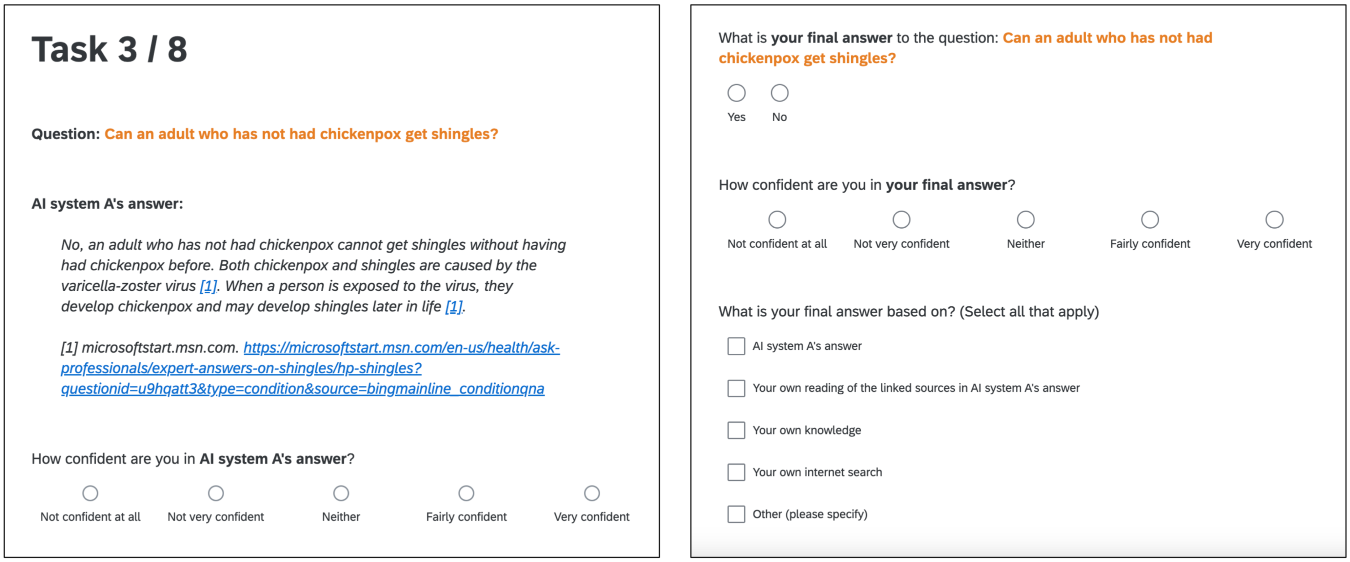


Figure 1: Screenshot of the information-seeking task (shown in the Control, Uncertain1st, and UncertainGeneral conditions). Additional screenshots, including the variant shown in the No-AI condition, can be found in Appendix D.

studied communicating the confidence of a conversational music recommendation system through language and color coding. Experimenting with different levels of calibration, they found that accurate confidence signals led to the greatest increase in trust without encouraging overreliance, though underreliance may still occur. Zhang et al. [106] explored different ways of having an AI system (named "ShapeBot") express confidence in the reasoning behind its recommendation, examining the effect of point of view (first-person "*I think...*" vs. third-person "*ShapeBot thinks...*") and strength of the belief expressed ("*ShapeBot thinks...*" vs. "*ShapeBot knows...*"). They found that both factors affected user reliance, highlighting the importance of carefully considering the language used to express (un)certainty.

2.2 Uncertainty in LLMs

Obtaining accurate numerical estimates of uncertainty for LLMs is an active line of research. One way to estimate an LLM's uncertainty is by the likelihood of generating a specific output given the context. However, this "generation probability" may not reflect what end users expect or want when they think of uncertainty [91]. A more useful notion of uncertainty might be one that captures how likely it is that the LLM's output is factually correct or correctly meets the user's needs. This notion of uncertainty may apply to a full output or to sentences, phrases, or words within the output. Many researchers are working on evaluating how calibrated existing uncertainty estimates are and proposing new techniques to improve calibration [4, 26, 31, 47, 51, 53, 67, 88, 110]. Current findings suggest that LLMs are often overconfident [26, 67, 103], which may give a false impression of their capabilities and exacerbate overreliance [34].

There is also a growing interest in LLMs' ability to directly generate natural language expressions of (un)certainty [51, 67, 103, 110]. Notably, Mielke et al. [67] observed that LLMs regularly express confidence (e.g., "*Obviously...*") and doubt (e.g., "*I'm not sure, but...*") through the language used in their outputs, but these expressions are poorly calibrated. Zhou et al. [110] "taught" OpenAI's GPT-3 [18] model to express (un)certainty through prompt engineering, but also found that the generated expressions were not well calibrated, especially those suggesting high certainty.

Despite this active research, there has been little empirical work examining the impact of uncertainty expression on users of LLM-infused systems. Notable exceptions are the works of Vasconcelos et al. [91] and Spatharioti et al. [84], who explored the effect of highlighting uncertain parts of LLM outputs in the context of code completion and search, respectively, and the concurrent work of Zhou et al. [109], who explored the effect of LLMs' natural language expressions of (un)certainty in the context of trivia question answering. These studies' results support uncertainty expression as a promising technique to encourage appropriate reliance, particularly when uncertainty estimates are well calibrated. Our work adds empirical knowledge on this topic through a large-scale, pre-registered experiment studying natural language uncertainty expressions in the context of LLM-infused search.

To avoid making assumptions of calibration or tying our experiment to a particular uncertainty estimation approach, we design our study to include both instances in which the system expresses uncertainty when it is incorrect and instances in which it expresses uncertainty when it is correct. By randomly varying whether or not uncertainty is expressed on any particular response, we are able to directly compare participants' behavior when uncertainty is and is not expressed.

2.3 Measuring Reliance and Trust

We hypothesize that whether or not an AI system expresses uncertainty — and if it does, the perspective in which the uncertainty is expressed — impacts user reliance and trust. We note that there are many definitions, measures, and factors of reliance and trust [27, 46, 90, 93, 107]. We use a combination of dependent variables and a mix of behavioral and self-reported measures to capture aspects most relevant to our research setting of LLM-infused search.

In the AI-assisted decision-making literature, many experiments follow the judge-advisor paradigm [15], presenting a participant with an AI-generated answer to a question and then asking the participant to provide their own answer, a set-up we adopt in our work. In this set-up, *agreement* between a participant's answer and that of the AI system is a commonly studied behavioral measure of reliance and trust [19, 22, 49, 55, 61, 69, 104, 108]. While this does not capture reliance or trust directly — the participant may have come up with the same answer on their own even without the AI system — comparing how often participants agree with the AI system's answers across experimental conditions gives a way of measuring whether they rely on the system differently across conditions. We use this measure in our work. We note that in some prior work, the participant is asked to provide an initial answer first before seeing that of the AI system [57, 58, 77, 81]. In these cases, other metrics like weight of advice can be used to more directly capture reliance. We do not adopt this set-up because we use questions we do not expect participants to be able to answer on their own.

To complement *agreement*, we examine participants' *confidence*, *source usage*, *trust intentions*, and *trust beliefs*. First, as in prior work [22, 29, 45, 61, 77], we ask participants to report their *confidence* both in the answer output by the AI system and in their own answer. Second, as an indirect measure of reliance and trust, we capture participants' *source usage* by both tracking whether or not participants click on the linked sources in the system's responses and asking them to self-report the resources that they based their final answer on. Finally, using responses collected in an exit questionnaire, we measure participants' *trust intentions* and *trust beliefs* using the scales developed by McKnight et al. [39]. Trust intentions refer to a participant's desire to use the system, while trust beliefs refer to their perceptions about the system's trustworthiness such as the system's perceived ability, benevolence, and integrity [64]. In general, the two are positively related [39], but Radensky et al. [80] found that they can be differently impacted by a system's expressed confidence. We measure both in our experiment to better understand the impact of the system's uncertainty expression.

We also measure two system facets that are known to impact trust: *perceived anthropomorphism* and *perceived transparency*. Participants may view the expression of uncertainty (especially first-person) as an inherently human behavior, leading to increased anthropomorphism. Recent work has expressed concern around anthropomorphism leading to over-trust [1, 83], a potential path for uncertainty expression to backfire. Uncertainty expression can also increase the system's perceived transparency [13], which is generally shown to enhance trust, whether or not appropriate [50].

In addition to reliance and trust, we also consider task performance as a dependent variable, measured as *correctness* of participants' answers and *time on task*. Both of these have been studied in prior work on AI-assisted decision making [48], as well as specifically for studying the effect of uncertainty expression [92].

We formally define the dependent variables in Section 3.2 and articulate hypotheses in Section 3.3.

3 METHODS

As described in Section 2.3, our experiment is designed to measure the impact of natural language expressions of an LLM's uncertainty on user reliance and trust. We do this in the context of information seeking in the medical domain. We pre-registered our experimental design, hypotheses, analysis plan, and data collection procedures before collecting data.[2] To complement our pre-registered analyses, we include exploratory analyses and a qualitative analysis of participants' free-form responses. The study was approved by our internal Institutional Review Board (IRB).

3.1 Procedure and Experimental Conditions

We designed a between-subjects experiment with some within-subjects comparisons, which we conducted on Qualtrics. Participants complete a set of information-seeking tasks. Each task involves determining the correct yes-or-no answer to a challenging, factual question in the medical domain with or without access to responses from a fictional LLM-infused search engine, "AI system A." The presence and form of system responses provided to participants depend on their experimental condition. Specifically, participants are randomly placed into one of four experimental conditions:

- Control: Participants see AI responses without any expression of uncertainty.
- Uncertain1st: Participants see AI responses and half of the time these responses include uncertainty expressed in the first person, with personal pronouns (e.g., "*I'm not sure, but it seems...*").
- UncertainGeneral: Participants see AI responses and half of the time these responses include uncertainty expressed in a general perspective, without personal pronouns (e.g., "*There is uncertainty, but it seems...*").
- No-AI: Participants are not told about the AI system and do not see AI responses.

Control is a baseline to which we compare the conditions Uncertain1st and UncertainGeneral to understand the impact of uncertainty expressions. No-AI is a second baseline to understand the impact of access to the AI system.

The experiment is divided into three components. In the first, participants are introduced to the study and to AI system A (if applicable). They are given several task comprehension questions and are asked to complete an example task.

In the second component, participants answer a total of eight questions (details in Section 3.4). They are told they can use any resources they want as in natural settings. For each question, participants, except for those in the No-AI condition, are provided with responses from AI system A (Figure 1). The system's yes-or-no answers within their responses are correct for only half the questions. In the Uncertain1st and UncertainGeneral conditions, the AI system expresses uncertainty in its answers for half the questions — we refer to them as *uncertain* answers versus *not uncertain* answers. We chose this breakdown to have sufficient data for each of the four possible scenarios of correct/incorrect answers with/without uncertainty expression. We randomize the order in which questions are presented, as well as the set of questions for which the AI system expresses uncertainty. However, since we based the AI system's

[2] Our pre-registration is viewable at https://osf.io/mnrp9.

answers on real responses from Copilot in Bing (see Section 3.4), the set of answers and their correctness are fixed.

In the final component, participants fill out an exit questionnaire about their experience with and perception of the AI system (if applicable), their background on LLMs, and basic demographic information; see Appendix D. Lastly, participants are debriefed and reminded that some of the AI responses they saw may have contained inaccurate information.

3.2 Dependent Variables

We now formally define the dependent variables (DVs) that we measured, motivated in Section 2.3. First, for each of the eight questions, we measured the following DVs based on participants' observed behavior:

- `Agree`: TRUE if the participant's final answer is the same as the AI system's answer; FALSE otherwise.
- `Correct`: TRUE if the participant's final answer is correct; FALSE otherwise.
- `Time`: Number of minutes from when the participant saw the task to when they clicked next.
- `LinkClick`: TRUE if the participant clicks on one or more links in the system's answer; FALSE otherwise.

We additionally measured the following DVs based on participants' self-reported ratings:

- `UseAI`: TRUE if the participant selected "AI system A's answer" in the question "What is your final answer based on? (Select all that apply)"; FALSE otherwise.
- `UseLink`: TRUE if they selected "Your own reading of the linked sources in AI system A's answer" in the above question; FALSE otherwise.
- `UseInternet`: TRUE if they selected "Your own Internet search" in the above question.; FALSE otherwise.
- `ConfidenceAI`: Rating on the question "How confident are you in AI system A's answer?" on a 5-point scale.
- `ConfidenceAnswer`: Rating on the question "How confident are you in your final answer?" on a 5-point scale.

Finally, based on responses to the exit questionnaire, we calculated the following indexes (all on a 5-point scale):

- `TrustBelief`: Average rating on six statements adapted from the trust scale by McKnight et al. [39].
- `TrustIntention`: Average rating on four statements adapted from the trust scale by McKnight et al. [39].
- `Anthropomorphism`: Average rating on four items from the Godspeed Questionnaire Series [8].
- `Transparency`: Average rating on two statements: "I feel I had a good understanding of what AI system A's answers were based on" and "I feel I had a good understanding of when AI system A's answers might be wrong."

Full details are in Appendix D. Note that some DVs were not applicable for the No-AI condition, where we measured only `Agree`, `Correct`, `Time`, `UseInternet`, and `ConfidenceAnswer`. Here we made one (and only one) minor deviation from our pre-registration by including `Agree`. Although participants in this condition do not see the AI system's answers, this gives us a baseline for how often participants would arrive at the same answer on their own.

3.3 Hypothesis & Analysis

We expected the presence and perspective of uncertainty expression to impact participants' reliance, trust, and performance. Formally, for each DV, we hypothesized that condition affects DV. For each repeatedly measured DV, we additionally hypothesized that whether or not uncertainty was expressed in a particular AI response affects DV. We tested our hypotheses with the following pre-registered, confirmatory analyses, for which we present results in Section 4.

We first test the main effect of the conditions with a **between-condition analysis**. For repeatedly measured DVs, we fit the model `DV ~ Condition + (1|participant) + (1|question)` with Control as the reference level for `Condition`. Then to compare the effects of the two conditions with uncertainty, we used a Wald test to test the equality of the corresponding coefficients. For DVs measured once in the exit questionnaire, we use analysis of variance (ANOVA) to compare means across the conditions. If significant, we conduct pairwise comparisons with a post-hoc Tukey test.

Next, we test the effect of uncertainty being expressed or not in a particular response with a **within-condition analysis** for conditions with uncertainty expression. For repeatedly measured DVs, we fit the model `DV ~ AIUncertain + (1|participant) + (1|question)`, where `AIUncertain` is TRUE if the AI response is uncertain and FALSE otherwise. We fit this model once for data from the Uncertain1st condition and once for data from UncertainGeneral.

We complement the confirmatory analyses with two additional analyses. First, we conduct an exploratory analysis of the effect of AI's uncertainty expression on over- and underreliance by separately analyzing cases where the AI system gave correct versus incorrect answers. Analysis details and results are presented in Section 5.1. Second, we conduct a thematic analysis [16, 17] of free-form responses from participants in the Uncertain1st and UncertainGeneral conditions describing their experience with and perception of the AI system. The first author drafted the codebook and conducted the initial coding, then discussed the results with all authors and refined the coding together. We describe how the AI system's uncertainty expression affected participants in Section 4 along with the quantitative results, and describe how participants interpreted the system's uncertainty expression in Section 5.2.

3.4 Questions and AI Responses Used

We selected a set of factual questions for participants to answer according to the following criteria: (1) most lay people should not know the answer; (2) the question and answer should not directly show up when using popular search engines; and (3) the answer can be objectively and automatically assessed. To satisfy the criteria, we constructed a set of yes/no medical questions. We began with questions from the MedQuAD dataset [10] and made minor modifications to some to increase the difficulty of finding an answer. We verified that each question does not show up as it is and can not be immediately answered using popular search engines, and consulted multiple sources to confirm the correct answer.

To create AI responses that are realistic and reflect the state-of-the-art in LLM-infused search, we input the selected questions into Microsoft's Copilot in Bing. All responses were obtained in July 2023. To keep the fluency, style, and content of responses as realistic as possible, we made only minor modifications such as presenting in-line citations using square brackets instead of superscripts (see Figure 1) and starting each response with "Yes" or "No" for consistency (most responses from Copilot in Bing did this already). We did not make substantive changes to the content.

To create the uncertain versions of the responses, we drew on Oba and Berger [72]. For UNCERTAIN1ST, we replaced the leading "Yes" or "No" with an expression of the form "*I'm not {certain, sure}, but {it seems to me, it seems like, I would guess, I'd guess that}*," selecting one phrase from each set of brackets. Similarly, for UNCERTAINGENERAL, we used an expression of the form "*{It's unclear, It's not clear, There is uncertainty}, but it seems like*." Current LLMs already output expressions such as "*I'm not sure, but*" and "*I'm not sure, but my guess is*" [67], so we believe these insertions preserve the realisticness of responses. The only difference between the three versions of the AI system's responses is the presence and perspective of uncertainty expression; their information content is otherwise identical.

We selected the final eight questions such that: (1) four questions have a correct answer of "Yes" and four have a correct answer of "No" so that always selecting "Yes" is no better or worse than random guessing; (2) the AI answers are correct for four and incorrect for four, so that always agreeing with the AI system is no better or worse than random guessing; (3) questions are not too easy to answer without access to the AI system (determined via piloting). The final set of questions used is provided in Appendix E along with the original responses from Copilot in Bing and our modified responses.

3.5 Data Collection and Participants

We conducted our experiment on Amazon Mechanical Turk (MTurk), a crowdsourcing platform widely used for human-subject experiments. Research has shown data from MTurk workers is comparable to data from other pools (e.g., commercial panels, social media, colleges) [12, 20, 23, 32, 63, 74], but recently there has been a decrease in data quality [28, 44, 60, 62, 94, 98]. Indeed, in pilot studies we found that a strong requirement on qualification was necessary to obtain meaningful data, with the highest quality data obtained when requiring a "Masters" qualification (granted by Amazon based on past performance). Since the pool of available participants with a Masters qualification is limited, we pre-registered a recruitment plan in which we would initially aim to recruit 432 (determined via a power analysis) U.S.-based MTurk workers with a Masters qualification, 99% or higher approval rating, and at least 2000 completed human intelligence tasks (HITs), removing the Masters requirement after 7 days if we were unable to meet our target sample size. In parallel, we implemented best practices to mitigate the use of bots and improve data quality, including CAPTCHAs, honeypot questions, speed checks, attention checks, and open-ended questions, which we used to define data exclusions.

We collected 656 complete responses over the course of two weeks in September 2023, of which we excluded 252 (38.4%) based on five pre-registered exclusion criteria. Our final sample consists of 404 responses: 104 in CONTROL, 92 in UNCERTAIN1ST, 94 in UNCERTAINGENERAL, and 114 in NO-AI. See Appendix B for more on our data collection procedures.

Participants were paid \$5 USD. The payment was determined based on the expected experiment duration of 20 minutes (estimated from pilot studies) and target hourly wage of \$15. The actual median experiment duration was 20.5 minutes, so on average, participants were paid \$14.80 per hour. See Appendix A for more information about participants.

4 RESULTS: CONFIRMATORY ANALYSIS

We now present the results of our pre-registered, confirmatory analyses. Tables 1 and 2 contain the between-condition and within-condition analysis results, respectively. We refer the reader to Section 3.2 for definitions of all DVs. We present the estimated means (and standard errors) from the fitted models, calculated without conditioning on the random effects, and represent binary variables in percentages. We use *significance* to refer to statistical significance at the level of $p < 0.05$.

4.1 Agreement with AI: `Agree`

We begin with the results of agreement, a commonly used behavioral measure of reliance and trust. Our first finding is that **people tend to agree with the AI system when its responses are provided**. Our between-condition analysis suggests that participants with access to the AI system are significantly more likely to submit the same answer as the system than those who do not have access (80.9% CONTROL vs. 58.4% NO-AI). We next find that **AI's uncertainty expression decreases agreement with the AI system**. Compared to CONTROL (80.9%), `Agree` is significantly lower in UNCERTAIN1ST (74.8%). It is also lower in UNCERTAINGENERAL (77.6%), although the difference is not significant. Our within-condition analysis suggests AI's uncertainty expression decreases agreement at the instance level as well. The estimated means of `Agree` for not uncertain vs. uncertain AI responses are 84.7% vs. 70.9% for UNCERTAINGENERAL (significantly different) and 79.5% vs. 73.4% for UNCERTAIN1ST (not significantly different). We find support for this finding in the qualitative data as well. 10 participants (out of 186 in UNCERTAIN1ST and UNCERTAINGENERAL) stated that when they disagreed with the system it was, as one put it, "*because of the uncertainty of the answers provided by AI*."

Other reasons participants mentioned for disagreement included the system's answer being different from their own knowledge (e.g., "*A couple of the AI's answers didn't make sense so from my own common sense I had to make my own judgement*") or the information in other resources (e.g., "*The answer seemed to contradict the links given, or I could not find how they came to that answer with the information from the links given*") and having lower trust in the system.

4.2 Confidence in Answers: `ConfidenceAI`, `ConfidenceAnswer`

Looking at participants' self-reported confidence in answers, we find that **AI's uncertainty expression decreases people's confidence in its answer**. Compared to CONTROL (3.95 on a 5-point scale), `ConfidenceAI` is significantly lower in UNCERTAIN1ST (3.66). It is also lower in UNCERTAINGENERAL (3.80), although the difference is not significant. Our within-condition analysis provides further evidence for this finding and suggests that **AI's uncertainty expression decreases people' confidence in their final answer**

Table 1: Between-condition analysis. We compare DVs across conditions. We report the model-estimated means (and standard errors) from our confirmatory analysis. The rightmost column shows pairs of conditions with statistically significant differences with significance marked as * ($p < 0.05$) or ** ($p < 0.01$).

†Note that we did not compare all possible pairs of conditions (see Section 3.3). For repeatedly measured DVs, we compared (Control vs. Uncertain1st/UncertainGeneral/No-AI) and (Uncertain1st vs. UncertainGeneral) but not (No-AI vs. Uncertain1st/UncertainGeneral) to reduce the number of hypothesis testing. For DVs measured once in the exit questionnaire, we first compared the means of (Control, Uncertain1st, UncertainGeneral) using ANOVA, then if significant, conducted pairwise comparisons.

Sec.	DV	Control	Uncertain1st	UncertainGeneral	No-AI	Significant differences†
4.1	`Agree` (%)	80.9% (5.5)	74.8% (6.7)	77.6% (6.2)	58.4% (8.5)	No-AI <** Control Uncertain1st <* Control
4.2	`ConfidenceAI` (1-5)	3.95 (0.17)	3.66 (0.17)	3.80 (0.17)		Uncertain1st <** Control
	`ConfidenceAnswer` (1-5)	4.30 (0.08)	4.34 (0.08)	4.27 (0.08)	4.22 (0.08)	
4.3	`LinkClick` (%)	2.7% (2.1)	7.2% (4.8)	3.9% (3.1)		
	`UseAI` (%)	77.3% (5.1)	64.8% (6.9)	72.3% (6.0)		
	`UseLink` (%)	74.7% (5.5)	85.5% (4.0)	81.7% (4.8)		
	`UseInternet` (%)	19.1% (5.6)	27.0% (7.4)	23.2% (6.7)	92.9% (2.5)	Control <** No-AI
4.4	`TrustBelief` (1-5)	3.90 (0.06)	3.86 (0.07)	4.00 (0.07)		
	`TrustIntention` (1-5)	3.25 (0.10)	2.91 (0.10)	3.36 (0.10)		Uncertain1st <* Control <* UncertainGeneral
	`Anthropomorphism` (1-5)	3.07 (0.10)	3.00 (0.11)	3.13 (0.11)		
	`Transparency` (1-5)	4.04 (0.06)	3.93 (0.07)	4.01 (0.07)		
4.5	`Correct` (%)	63.9% (8.6)	72.8% (7.4)	67.9% (8.1)	74.2% (7.1)	Control <** Uncertain1st Control <** No-AI
	`Time` (min)	2.13 (0.22)	2.10 (0.23)	2.03 (0.22)	1.57 (0.21)	No-AI <* Control

at the instance level. For both Uncertain1st and UncertainGeneral, `ConfidenceAI` and `ConfidenceAnswer` are significantly lower on instances with uncertain (vs. not uncertain) AI responses. Indeed, one participant in the Uncertain1st condition stated, "*If the AI didn't seem confident, I would like [sic] on the links. If the AI seemed confident I assumed he was correct most of the time.*"

4.3 Source Usage: `LinkClick`, `UseAI`, `UseLink`, `UseInternet`

Looking at source usage, we find that **people with access to the AI system conduct their own Internet search less frequently than those without access**. `UseInternet` is notably lower in Control (19.1%) than No-AI (92.9%). However, we see no significant differences in source usage between the three conditions in which AI responses are present, meaning **there is no evidence that the presence and perspective of AI's uncertainty expression affect people's source usage behavior**. On the other hand, from our within-condition analysis, we find that AI's uncertainty expression has a significant effect on the self-reported DVs at the instance level. On instances with uncertain AI responses (vs. not uncertain responses), `UseAI` is significantly lower in both Uncertain1st and UncertainGeneral, and `UseInternet` is significantly higher in Uncertain1st. These results suggest that **at the instance level, AI's uncertainty expression decreases the use of the system's answer and increases the use of other resources.** In their free-form responses, 11 participants stated that the system's uncertainty motivated them to verify information using the links provided in the answer (e.g., "*I clicked on the links provided when the AI was uncertain of the answers*") while 13 mentioned it motivated them to perform their own search (e.g., "*When the AI wasn't certain, I searched on Google*").

We note that both `LinkClick` and `UseLink` are intended to capture whether or not participants read the linked sources provided in the AI system's responses, but the estimated means of `LinkClick` (2.7% – 7.2%) from the between-condition analysis are much lower than those of `UseLink` (74.7% — 85.5%). There are several factors that might contribute to this discrepancy. First, these estimated means are from different models that include participants and questions as random effects. The intercepts for random effects in these models are quite high. Looking at the raw data, there is still a gap, but not as large: the actual means are 30.6% – 34.9% for `LinkClick` and 64.2% – 71.6% for `UseLink`. Second, there could have been measurement error from self-report bias for `UseLink` [35]. Finally, some participants could have considered their answers to be based on their "own reading of the linked sources" if they read the list of links, even if they didn't click to open them. For example, one participant wrote, "*If the link title gave the same answer as the AI answer, then I assumed it was the right answer.*" This discrepancy emphasizes the value of including both behavioral and self-reported measures.

Table 2: Within-condition analysis. For each of the two conditions with uncertainty, we compare DVs measured on instances with AI answers that are not uncertain vs. uncertain. We report the model-estimated means (and standard errors) from our confirmatory analysis. > and < note statistically significant differences with significance marked as * ($p < 0.05$) or ** ($p < 0.01$).

†The model does not fit properly due to large individual variance which we discuss in an exploratory analysis in Appendix C.1.

Sec.	DV	Uncertain1st			UncertainGeneral		
		Not Uncertain		Uncertain	Not Uncertain		Uncertain
4.1	`Agree` (%)	79.5% (7.2)		73.4% (8.6)	84.7% (5.0)	>**	70.9% (7.8)
4.2	`ConfidenceAI` (1-5)	3.88 (0.20)	>**	3.44 (0.20)	3.95 (0.16)	>**	3.65 (0.16)
	`ConfidenceAnswer` (1-5)	4.42 (0.09)	>**	4.26 (0.09)	4.36 (0.07)	>**	4.18 (0.07)
4.3	`LinkClick` (%)	14.3% (6.9)		9.9% (5.1)	*See table caption*†		
	`UseAI` (%)	73.2% (7.2)	>**	57.4% (8.9)	79.7% (4.7)	>**	62.9% (6.5)
	`UseLink` (%)	86.5% (4.2)		84.3% (4.7)	*See table caption*†		
	`UseInternet` (%)	23.0% (6.3)	<**	34.1% (7.8)	19.2% (6.5)		26.9% (8.1)
4.5	`Correct` (%)	73.6% (8.9)		75.7% (8.4)	69.4% (10.1)		70.3% (9.9)
	`Time` (min)	2.00 (0.29)		2.19 (0.29)	1.84 (0.25)	<*	2.23 (0.25)

4.4 Trust and Perception of AI: `TrustBelief`, `TrustIntention`, `Anthropomorphism`, `Transparency`

Moving onto trust and perception of AI, we find that **the presence and perspective of uncertainty expression neither affect people's trust beliefs nor the perceived anthropomorphism and transparency of the system.** There are no significant differences in `TrustBelief`, `Anthropomorphism`, and `Transparency` between Control and the two conditions with uncertainty. Overall, participants had **somewhat positive trust beliefs** about the system (`TrustBelief` is around "4: Somewhat agree" for all conditions); reported that they had a **somewhat good understanding of what the AI system's answers were based on and when they might be wrong** (`Transparency` is around "4: Somewhat agree"); and had **neutral perceptions of anthropomorphism** (`Anthropomorphism` is around "3: Neutral").

In contrast, we find that **first-person expressions of uncertainty decrease trust intentions while expressions from a general perspective do not**. `TrustIntention` is significantly lower in Uncertain1st (2.91) compared to both Control (3.25) and UncertainGeneral (3.36), indicating a lower desire to use the system. Illustrative of this, one participant in the Uncertain1st condition stated, "*[The AI system] was very non-committal in its answers so I didn't feel I could trust it.*" This suggests that frequent first-person expressions of uncertainty can lead people to view the system as less trustworthy and decrease their desire to use it. More about the used scales and item-level results is in Appendix C.2.

4.5 Task Performance: `Correct`, `Time`

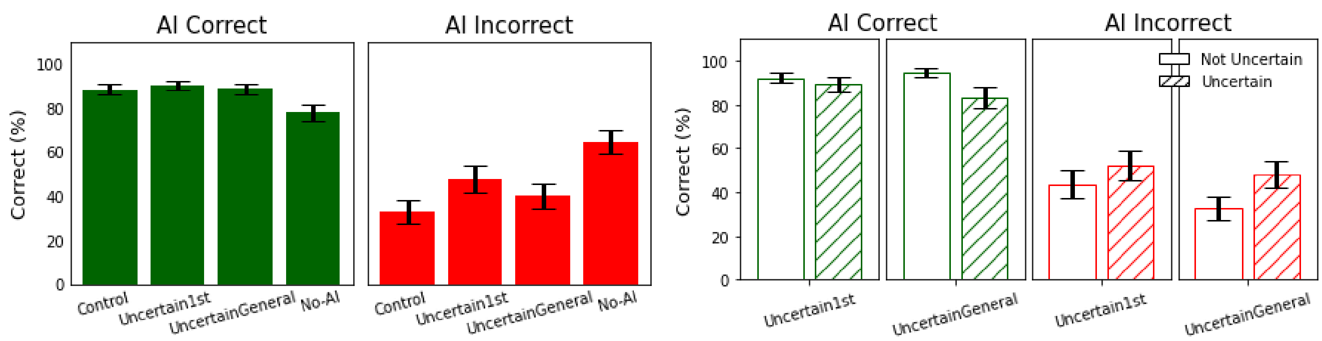
Finally, we analyze participants' task performance. From our between-condition analysis of `Correct`, we first find that **having access to the AI system decreases people's accuracy**. Participants with access to the system have significantly lower accuracy than those without (63.9% Control vs. 74.2% No-AI). However, this result should be interpreted in the context of the AI system's low overall accuracy (50.0% in our experimental setup). Second, we find that **AI's uncertainty expression increases people's accuracy**. `Correct` is significantly higher in Uncertain1st (72.8%) than Control (63.9%). It is also higher in UncertainGeneral (67.9%), but the difference is not significant.

From our between-condition analysis of `Time`, we find that **having access to the AI system increases task time**. `Time` is significantly higher in Control (2.13 min) than No-AI (1.57 min). Together with the results on correctness, this suggests that **having access to the AI system decreases overall performance in our experimental setup**. Between Control and the two conditions with uncertainty, there are no significant differences in task time. However, our within-condition analysis suggests that **AI's uncertainty expression increases task time at the instance level**. The estimated means of `Time` for not uncertain vs. uncertain AI responses are 1.84 min vs. 2.23 min for UncertainGeneral (significantly different) and 2.00 min vs. 2.19 min for Uncertain1st (not significantly different). An explanation of this result is that AI's uncertainty expression slows people down to use more caution when completing the task.

5 RESULTS: ADDITIONAL ANALYSES

5.1 Effect of Uncertainty Expression on Over- and Underreliance

In Section 4.1, we analyzed participants' agreement with the AI system as a measure of reliance. Agreement can be appropriate or inappropriate, depending on the correctness of the AI system's answers; agreeing with the system when it is incorrect is a sign of overreliance, whereas disagreeing with it when it is correct is a sign of underreliance. To better understand the extent to which uncertainty expression leads to either of these phenomena, we take inspiration from the analysis of Chen et al. [25] and separately analyze participants' agreement on questions the AI system answers correctly and questions it answers incorrectly. Note that, having conditioned on the (in)correctness of the AI system, analyzing agreement is equivalent to analyzing correctness of people's final answers. We present the results here in terms of correctness to focus attention on whether reliance is appropriate (i.e., beneficial to the user) or not.



(a) Between-condition analysis results.

(b) Within-condition analysis results.

Figure 2: Exploratory analysis of over- and underreliance (Section 5.1). We analyze `Correct` (%) separately for questions the system answered correctly vs. incorrectly. We show the model-estimated means and standard errors for each condition (Figure 2a) and for not uncertain vs. uncertain responses in the conditions with uncertainty (Figure 2b).

Concretely, we run similar analyses to those presented in Section 4.5, but fit the regression models once on data from the four questions the system answered correctly and once on data from the four questions the system answered incorrectly (see Section 3.4). We show the estimated means (and standard errors) from these models in Figure 2.

First, by comparing the Control and No-AI conditions, we observe that having access to the AI system's answer increases accuracy when the system is correct (the estimated mean of `Correct` is 88.5% in Control vs. 77.9% in No-AI), but decreases accuracy when it is incorrect (33.0% in Control vs. 64.7% in No-AI), as in Figure 2a. Comparing Control with Uncertain1st and UncertainGeneral, we see that having the AI system express uncertainty improves accuracy on questions that the system answers incorrectly without reducing accuracy when the system is correct. In line with our earlier results, expressing uncertainty in the first-person perspective leads to a bigger improvement in accuracy when the AI system is incorrect compared with expressing uncertainty in the general perspective.

To better understand how expressions of uncertainty drive accuracy, we break down the results further, comparing task accuracy on questions for which the system expresses uncertainty and those for which it does not (Figure 2b). We find that expressing uncertainty about a particular question leads to some reduction in accuracy when the AI system is correct (92.2% to 89.2% for Uncertain1st, 94.8% to 83.1% for UncertainGeneral), but a greater increase in accuracy when the AI system is incorrect (43.6% to 52.0% for Uncertain1st, 32.8% to 48.0% for UncertainGeneral).

While these results provide some evidence that expressions of uncertainty help reduce overreliance, we note that participants in the Uncertain1st and UncertainGeneral conditions still have substantially lower accuracy on questions where the AI system is incorrect compared with participants in the No-AI condition.

5.2 Participants' Interpretations of AI's Uncertainty Expression

While our quantitative results shed light on whether expressions of uncertainty impact reliance and trust, they cannot tell us why. We next explore participants' interpretations of the expressed uncertainty via a thematic analysis of free-form responses to the question "When and why do you think AI system A expresses uncertainty?" in the exit questionnaire.

The majority of participants (N=102 of the 186 in the conditions with uncertainty) attributed the system's expressed uncertainty to its inability to answer a particular question, for example because it could not find an answer, found conflicting or unreliable answers, or could not understand the information it found. Three suggested the system was programmed to express uncertainty, as in "*I would guess there's some sort of certainty variable and if the score is below a level, an uncertainty message is included in the result.*" Another ten suggested the expressed uncertainty is due to the inherent difficulty of the question. As one put it, "*It could be a question that is very hard to come up with a simple yes or no answer.*"

These interpretations are all in line with the goal of reducing overreliance: if the system is unable to answer a question or the question is inherently difficult, users should verify the answer for themselves. Five participants explicitly interpreted the expressed uncertainty as a way of encouraging users to check their answers, for example, "*I suppose the AI wanted us to do further research in those cases where it could not be 100% sure of the answer.*"

A small number of participants attributed the uncertainty to other reasons, such as impression management ("*to appear more human, encourage confidence, and appear thoughtful*"), maintaining credibility ("*It doesn't want to risk being wrong on something and ruining it's credibility*"), avoiding liability ("*it expresses uncertainty to absolve it of responsibility in the event it is wrong*"), or restrictions on answering medical questions ("*the AI is programmed not to dispense medical advice which could potentially be harmful without a caveat*"). These interpretations may not necessarily reduce overreliance.

One might ask whether participants interpreted the two types of uncertainty expression differently. Indeed, we found that participants in the UncertainGeneral condition were more likely than those in Uncertain1st (51.5% vs. 41.3%) to attribute the uncertainty to the AI system finding conflicting or unreliable information or the question being inherently hard, whereas those in Uncertain1st were more likely (20.7% vs. 7.4%) to attribute it to limitations of the AI system itself.

6 DISCUSSION

Our results suggest that expressing uncertainty through natural language can be an effective way to reduce overreliance and (over)trust in LLM-infused search engines. Expressions of uncertainty led to more cautious behaviors, from taking longer to arrive at an answer to reporting more reliance on outside sources. However, it did not fully eliminate overreliance; the participants with the highest task performance were those without access to AI responses.

We find that perspective matters: uncertainty expressions in first-person show stronger effects than general perspective. This is consistent with prior findings that first-person messages increase recipients' involvement and engagement [24, 106] compared with general or third-person messages. This persuasive effect of first-person expressions should be interpreted with caution: while it helps heighten the warning effect of a negative message such as uncertainty, it might amplify a positive message, even if unjustified. For example, one may want to avoid first-person expressions of *confidence* because they may exacerbate overreliance and overtrust, as found in prior work [109]. There are also concerns around harms from anthropomorphism of AI systems that may stem from over-trust, deception, threats to human agency, and propagation of stereotypes [1]. While we did not observe that first-person uncertainty expression increases perceived anthropomorphism, people can start assigning social attributes to machines without conscious awareness [71]. Future research and practices should further explore the long-term effects of interacting with AI systems expressing uncertainty in a first-person perspective and consider other potential negative effects of anthropomorphism.

Our research has implications both for those building and deploying LLMs and LLM-infused applications and for policymakers regulating the use of AI. Most critically, any approach to reducing overreliance should be validated through empirical research. There may also be tradeoffs when balancing over- and underreliance. In our study, the most successful approach to reducing overreliance was to use first-person uncertainty expression, but this also decreased participant trust in the AI system, which may be undesirable in settings where people already under-trust the AI system. We believe there is no one-size-fits-all approach to implementing natural language uncertainty expression. For these reasons, given that the issue of how to manage overreliance is of particular importance to regulators, we advocate for raising awareness of the complexities of mitigating overreliance and for customized, evidence-based solutions, rather that universal ones.

There are limitations to our research. The widespread deployment of LLMs is still relatively new and the human-computer interaction and broader research communities are still grappling with the question of how to design effective studies to understand how end users perceive and interact with them. There is always a tradeoff between the controllability of the experiment and the generalizability of the conclusions to user behaviors in their day-to-day tasks [65]. In order to be able to measure agreement and correctness, we adopted an experimental set-up inspired by the AI-assisted decision-making literature in which study participants provide simple yes/no answers to questions. This approach does not allow exploring how the expression of uncertainty would impact people's behavior when completing more complex tasks, like writing an article or planning a trip. Further, our measurements of time and source usage are less reliable than they would have been had we opted for an in-person lab study. We chose questions from the medical domain, where overreliance is particularly concerning, but people may behave differently when seeking information about their own medical symptoms rather than answering a pre-defined set of questions. People may also behave differently when given the chance to interact with the system repeatedly as opposed to in a single session. The AI system in our study exhibited low accuracy and expressed uncertainty often, in a poorly calibrated manner. These design choices may have impacted our results — particularly the lower task performance when given access to the AI system. Also, there may be differences across cultures and languages in how people interpret or react to uncertainty. Our study was conducted in English with U.S.-based participants and results may not generalize to other cultural and linguistic contexts.

For all of these reasons, while our findings suggest that natural language expressions of uncertainty could be an effective approach to reducing overreliance, we caution against overgeneralizing from our study. Instead, we view our results as evidence that language choices matter in how people perceive and act on the outputs of LLMs, and teams building and deploying LLMs should therefore evaluate them carefully with end users before release.

7 ETHICAL CONSIDERATIONS AND POSITIONALITY

We conclude with a reflection on the ethical considerations of our work and our positionality.

Mitigating harms to human subjects. We recruited U.S.-based participants on MTurk, which many people rely on as a primary source of income. As discussed in Section 3.5, we aimed to provide an hourly wage of $15 USD. We came close to this goal, with participants receiving an estimated $14.80 per hour on average. (This is likely an underestimate of average wage, since we have no way to know if workers spent time on other activities between accepting the task and completing it.) This is substantially higher than the U.S. federal minimum wage of $7.25 per hour, though a few states have recently adopted a minimum wage of $15/hour or higher. As discussed in the FAccT 2023 panel "The Humans Behind the Intelligence: Speaking with Data Workers," our choice to limit participation to workers with a 99% or higher approval rating, at least 2000 completed tasks, and in some cases, a Masters qualification, prevented workers who are new to MTurk from participating. We made the decision to include these qualifications after piloting several versions of the study with less restrictive qualifications and finding that the data quality was too poor to use. We paid and approved the work of everyone who completed the study, regardless of whether their responses passed our quality checks. At the end of the study, we debriefed participants, reminding them that the medical information output by the AI system was sometimes incorrect. We did not collect personally identifiable information except for MTurk IDs, which were used to ensure that workers who participated in pilots of our study did not participate in the main study. These were deleted when no longer needed. Our procedure was reviewed and approved by our internal IRB and we obtained participant consent.

Potential negative societal impact. While our results provide evidence for the effectiveness of natural language expressions of uncertainty for reducing overreliance, generalizing too heavily from our findings could lead to potential harms. Given the limitations of our research (see Section 6), teams deploying LLMs or LLM-infused applications should not make decisions about how to express uncertainty to end users without extensive user testing in their own contexts. They also should not assume that they have addressed overreliance by expressing uncertainty. (Indeed, in our study we see that participants still have higher task performance with no access to the AI system.) Likewise, regulators should avoid making blanket requirements on uncertainty expression, at least until more research has been done.

Separate from these potential unintentional misuses of our research, there is a possibility that bad actors could strategically incorporate the expression of uncertainty into an LLM's output to make them more persuasive, regardless of whether they represent objective fact, potentially contributing to the spread of misinformation.

Positionality. Our research questions and design were influenced by our position as employees of a U.S.-based technology company. Members of our research team have first-hand experience observing and participating in discussions regarding the responsible development and deployment of LLM-infused applications, which has shaped our understanding of gaps in knowledge and other practical challenges that arise in attempting to meet responsible AI principles and proposed regulatory requirements. We had access to sufficient budget to run large-scale experiments, which is not an option for some research teams. Our view that there are potential benefits of responsibly deployed LLM-infused applications is likely influenced by our experience in industry, yet we acknowledge some fundamental limitations of using LLMs for information retrieval [82]. We encourage future research on overreliance from research teams in academia and civil society.

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REFERENCES

[1] Gavin Abercrombie, Amanda Cercas Curry, Tanvi Dinkar, Verena Rieser, and Zeerak Talat. 2023. Mirages. On Anthropomorphism in Dialogue Systems. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, Houda Bouamor, Juan Pino, and Kalika Bali (Eds.). Association for Computational Linguistics, Singapore, 4776–4790. https://doi.org/10.18653/v1/2023.emnlp-main.290

[2] Perplexity AI. 2023. Announcing our series A funding round and mobile app launch. https://www.perplexity.ai/blog

[3] Naser Al Madi. 2022. How readable is model-generated code? Wxamining readability and visual inspection of github copilot. In *Proceedings of the 37th IEEE/ACM International Conference on Automated Software Engineering*. 1–5.

[4] Alfonso Amayuelas, Liangming Pan, Wenhu Chen, and William Wang. 2023. Knowledge of Knowledge: Exploring Known-Unknowns Uncertainty with Large Language Models. arXiv:2305.13712 [cs.CL]

[5] Zahra Ashktorab, Mohit Jain, Q. Vera Liao, and Justin D. Weisz. 2019. Resilient Chatbots: Repair Strategy Preferences for Conversational Breakdowns. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–12. https://doi.org/10.1145/3290605.3300484

[6] Joris Baan, Nico Daheim, Evgenia Ilia, Dennis Ulmer, Haau-Sing Li, Raquel Fernández, Barbara Plank, Rico Sennrich, Chrysoula Zerva, and Wilker Aziz. 2023. Uncertainty in Natural Language Generation: From Theory to Applications. arXiv:2307.15703 [cs.CL]

[7] Gagan Bansal, Tongshuang Wu, Joyce Zhou, Raymond Fok, Besmira Nushi, Ece Kamar, Marco Tulio Ribeiro, and Daniel Weld. 2021. Does the Whole Exceed Its Parts? The Effect of AI Explanations on Complementary Team Performance. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 81, 16 pages. https://doi.org/10.1145/3411764.3445717

[8] Christoph Bartneck, Dana Kulić, Elizabeth Croft, and Susana Zoghbi. 2009. Measurement Instruments for the Anthropomorphism, Animacy, Likeability, Perceived Intelligence, and Perceived Safety of Robots. *International Journal of Social Robotics* 1, 1 (2009), 71–81.

[9] Sarah Belia, Fiona Fidler, Jennifer Williams, and Geoff Cumming. 2005. Researchers misunderstand confidence intervals and standard error bars. *Psychology Methods* 10, 4 (2005), 389–396. https://doi.org/10.1037/1082-989X.10.4.389

[10] Asma Ben Abacha and Dina Demner-Fushman. 2019. A Question-Entailment Approach to Question Answering. *BMC Bioinform.* 20, 1 (2019), 511:1–511:23. https://bmcbioinformatics.biomedcentral.com/articles/10.1186/s12859-019-3119-4

[11] Emily M. Bender, Timnit Gebru, Angelina McMillan-Major, and Shmargaret Shmitchell. 2021. On the Dangers of Stochastic Parrots: Can Language Models Be Too Big?. In *Proceedings of the 2021 ACM Conference on Fairness, Accountability, and Transparency* (Virtual Event, Canada) *(FAccT '21)*. Association for Computing Machinery, New York, NY, USA, 610–623. https://doi.org/10.1145/3442188.3445922

[12] Adam Berinsky, Gregory Huber, Gabriel Lenz, and R. Alvarez. 2012. Evaluating Online Labor Markets for Experimental Research: Amazon.com's Mechanical Turk. *Political Analysis* 20 (07 2012), 351–368. https://doi.org/10.2307/23260322

[13] Umang Bhatt, Javier Antorán, Yunfeng Zhang, Q. Vera Liao, Prasanna Sattigeri, Riccardo Fogliato, Gabrielle Melançon, Ranganath Krishnan, Jason Stanley, Omesh Tickoo, Lama Nachman, Rumi Chunara, Madhulika Srikumar, Adrian Weller, and Alice Xiang. 2021. Uncertainty as a Form of Transparency: Measuring, Communicating, and Using Uncertainty. In *Proceedings of the 2021 AAAI/ACM Conference on AI, Ethics, and Society* (Virtual Event, USA) *(AIES '21)*. Association for Computing Machinery, New York, NY, USA, 401–413. https://doi.org/10.1145/3461702.3462571

[14] Rishi Bommasani, Drew A. Hudson, Ehsan Adeli, Russ Altman, Simran Arora, Sydney von Arx, Michael S. Bernstein, Jeannette Bohg, Antoine Bosselut, Emma Brunskill, Erik Brynjolfsson, S. Buch, Dallas Card, Rodrigo Castellon, Niladri S. Chatterji, Annie S. Chen, Kathleen A. Creel, Jared Davis, Dora Demszky, Chris Donahue, Moussa Doumbouya, Esin Durmus, Stefano Ermon, John Etchemendy, Kawin Ethayarajh, Li Fei-Fei, Chelsea Finn, Trevor Gale, Lauren E. Gillespie, Karan Goel, Noah D. Goodman, Shelby Grossman, Neel Guha, Tatsunori Hashimoto, Peter Henderson, John Hewitt, Daniel E. Ho, Jenny Hong, Kyle Hsu, Jing Huang, Thomas F. Icard, Saahil Jain, Dan Jurafsky, Pratyusha Kalluri, Siddharth Karamcheti, Geoff Keeling, Fereshte Khani, O. Khattab, Pang Wei Koh, Mark S. Krass, Ranjay Krishna, Rohith Kuditipudi, Ananya Kumar, Faisal Ladhak, Mina Lee, Tony Lee, Jure Leskovec, Isabelle Levent, Xiang Lisa Li, Xuechen Li, Tengyu Ma, Ali Malik, Christopher D. Manning, Suvir P. Mirchandani, Eric Mitchell, Zanele Munyikwa, Suraj Nair, Avanika Narayan, Deepak Narayanan, Benjamin Newman, Allen Nie, Juan Carlos Niebles, Hamed Nilforoshan, J. F. Nyarko, Giray Ogut, Laurel Orr, Isabel Papadimitriou, Joon Sung Park, Chris Piech, Eva Portelance, Christopher Potts, Aditi Raghunathan, Robert Reich, Hongyu Ren, Frieda Rong, Yusuf H. Roohani, Camilo Ruiz, Jack Ryan, Christopher R'e, Dorsa Sadigh, Shiori Sagawa, Keshav Santhanam, Andy Shih, Krishna Parasuram Srinivasan, Alex Tamkin, Rohan Taori, Armin W. Thomas,

Florian Tramèr, Rose E. Wang, William Wang, Bohan Wu, Jiajun Wu, Yuhuai Wu, Sang Michael Xie, Michihiro Yasunaga, Jiaxuan You, Matei A. Zaharia, Michael Zhang, Tianyi Zhang, Xikun Zhang, Yuhui Zhang, Lucia Zheng, Kaitlyn Zhou, and Percy Liang. 2021. On the Opportunities and Risks of Foundation Models. *ArXiv* (2021). https://crfm.stanford.edu/assets/report.pdf

[15] Silvia Bonaccio and Reeshad S Dalal. 2006. Advice taking and decision-making: An integrative literature review, and implications for the organizational sciences. *Organizational behavior and human decision processes* 101, 2 (2006), 127–151.

[16] Richard E Boyatzis. 1998. *Transforming qualitative information: Thematic analysis and code development.* sage.

[17] Virginia Braun and Victoria Clarke. 2006. Using thematic analysis in psychology. *Qualitative Research in Psychology* 3, 2 (2006), 77–101. https://doi.org/10.1191/1478088706qp063oa

[18] Tom Brown, Benjamin Mann, Nick Ryder, Melanie Subbiah, Jared D Kaplan, Prafulla Dhariwal, Arvind Neelakantan, Pranav Shyam, Girish Sastry, Amanda Askell, Sandhini Agarwal, Ariel Herbert-Voss, Gretchen Krueger, Tom Henighan, Rewon Child, Aditya Ramesh, Daniel Ziegler, Jeffrey Wu, Clemens Winter, Chris Hesse, Mark Chen, Eric Sigler, Mateusz Litwin, Scott Gray, Benjamin Chess, Jack Clark, Christopher Berner, Sam McCandlish, Alec Radford, Ilya Sutskever, and Dario Amodei. 2020. Language Models are Few-Shot Learners. In *Advances in Neural Information Processing Systems*, H. Larochelle, M. Ranzato, R. Hadsell, M.F. Balcan, and H. Lin (Eds.), Vol. 33. Curran Associates, Inc., 1877–1901. https://proceedings.neurips.cc/paper_files/paper/2020/file/1457c0d6bfcb4967418bfb8ac142f64a-Paper.pdf

[19] Zana Buçinca, Maja Barbara Malaya, and Krzysztof Z. Gajos. 2021. To Trust or to Think: Cognitive Forcing Functions Can Reduce Overreliance on AI in AI-Assisted Decision-Making. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW1, Article 188 (apr 2021), 21 pages. https://doi.org/10.1145/3449287

[20] Michael Buhrmester, Tracy Kwang, and Samuel Gosling. 2011. Amazon's Mechanical Turk: A New Source of Inexpensive, Yet High-Quality, Data? *Perspectives on Psychological Science* 6 (02 2011), 3–5. https://doi.org/10.1177/1745691610393980

[21] Carrie J. Cai, Samantha Winter, David Steiner, Lauren Wilcox, and Michael Terry. 2019. "Hello AI": Uncovering the Onboarding Needs of Medical Practitioners for Human-AI Collaborative Decision-Making. *Proc. ACM Hum.-Comput. Interact.* 3, CSCW, Article 104 (nov 2019), 24 pages. https://doi.org/10.1145/3359206

[22] Shiye Cao and Chien-Ming Huang. 2022. Understanding User Reliance on AI in Assisted Decision-Making. *Proc. ACM Hum.-Comput. Interact.* 6, CSCW2, Article 471 (nov 2022), 23 pages. https://doi.org/10.1145/3555572

[23] Krista Casler, Lydia Bickel, and Elizabeth Hackett. 2013. Separate but equal? A comparison of participants and data gathered via Amazon's MTurk, social media, and face-to-face behavioral testing. *Computers in Human Behavior* 29, 6 (2013), 2156–2160. https://doi.org/10.1016/j.chb.2013.05.009

[24] Meng Chen, Robert A Bell, and Laramie D Taylor. 2017. Persuasive effects of point of view, protagonist competence, and similarity in a health narrative about type 2 diabetes. *Journal of health communication* 22, 8 (2017), 702–712.

[25] Valerie Chen, Q. Vera Liao, Jennifer Wortman Vaughan, and Gagan Bansal. 2023. Understanding the Role of Human Intuition on Reliance in Human-AI Decision-Making with Explanations. *Proc. ACM Hum.-Comput. Interact.* 7, CSCW2, Article 370 (oct 2023). https://doi.org/10.1145/3610219

[26] Yangyi Chen, Lifan Yuan, Ganqu Cui, Zhiyuan Liu, and Heng Ji. 2023. A Close Look into the Calibration of Pre-trained Language Models. In *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Association for Computational Linguistics, Toronto, Canada, 1343–1367. https://doi.org/10.18653/v1/2023.acl-long.75

[27] Yang Cheng and Zifei Fay Chen. 2021. Encountering misinformation online: Antecedents of trust and distrust and their impact on the intensity of Facebook use. 45, 2 (2024/04/10 2021), 372–388.

[28] Michael Chmielewski and Sarah C. Kucker. 2020. An MTurk Crisis? Shifts in Data Quality and the Impact on Study Results. *Social Psychological and Personality Science* 11, 4 (2020), 464–473. https://doi.org/10.1177/1948550619875149

[29] Leah Chong, Guanglu Zhang, Kosa Goucher-Lambert, Kenneth Kotovsky, and Jonathan Cagan. 2022. Human confidence in artificial intelligence and in themselves: The evolution and impact of confidence on adoption of AI advice. *Computers in Human Behavior* 127 (2022), 107018. https://doi.org/10.1016/j.chb.2021.107018

[30] Dominic A. Clark. 1990. Verbal uncertainty expressions: A critical review of two decades of research. *Current Psychology* 9, 3 (1990), 203–235.

[31] Jeremy Cole, Michael Zhang, Daniel Gillick, Julian Eisenschlos, Bhuwan Dhingra, and Jacob Eisenstein. 2023. Selectively Answering Ambiguous Questions. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, Houda Bouamor, Juan Pino, and Kalika Bali (Eds.). Association for Computational Linguistics, Singapore, 530–543. https://doi.org/10.18653/v1/2023.emnlp-main.35

[32] Alexander Coppock. 2019. Generalizing from Survey Experiments Conducted on Mechanical Turk: A Replication Approach. *Political Science Research and Methods* 7, 3 (2019), 613–628.

[33] Mandeep K. Dhami and David R. Mandel. 2022. Communicating uncertainty using words and numbers. *Trends in Cognitive Sciences* 26, 6 (2023/11/20 2022), 514–526.

[34] Emily Dinan, Gavin Abercrombie, A. Bergman, Shannon Spruit, Dirk Hovy, Y-Lan Boureau, and Verena Rieser. 2022. SafetyKit: First Aid for Measuring Safety in Open-domain Conversational Systems. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Association for Computational Linguistics, Dublin, Ireland, 4113–4133. https://doi.org/10.18653/v1/2022.acl-long.284

[35] Stewart I. Donaldson and Elisa J. Grant-Vallone. 2002. Understanding Self-Report Bias in Organizational Behavior Research. *Journal of Business and Psychology* 17, 2 (2002), 245–260.

[36] Amanda M. Durik, M. Anne Britt, Rebecca Reynolds, and Jennifer Storey. 2008. The Effects of Hedges in Persuasive Arguments: A Nuanced Analysis of Language. *Journal of Language and Social Psychology* 27, 3 (2008), 217–234. https://doi.org/10.1177/0261927X08317947

[37] Asbjørn Følstad and Cameron Taylor. 2020. Conversational Repair in Chatbots for Customer Service: The Effect of Expressing Uncertainty and Suggesting Alternatives. In *Chatbot Research and Design*, Asbjørn Følstad, Theo Araujo, Symeon Papadopoulos, Effie Lai-Chong Law, Ole-Christoffer Granmo, Ewa Luger, and Petter Bae Brandtzaeg (Eds.). Springer International Publishing, Cham, 201–214.

[38] Katy Ilonka Gero, Tao Long, and Lydia B Chilton. 2023. Social Dynamics of AI Support in Creative Writing. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) *(CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 245, 15 pages. https://doi.org/10.1145/3544548.3580782

[39] D. Harrison McKnight, Vivek Choudhury, and Charles Kacmar. 2002. The impact of initial consumer trust on intentions to transact with a web site: a trust building model. *The Journal of Strategic Information Systems* 11, 3 (2002), 297–323. https://doi.org/10.1016/S0963-8687(02)00020-3

[40] Jake M. Hofman, Daniel G. Goldstein, and Jessica Hullman. 2020. How Visualizing Inferential Uncertainty Can Mislead Readers About Treatment Effects in Scientific Results. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. https://doi.org/10.1145/3313831.3376454

[41] Ziwei Ji, Nayeon Lee, Rita Frieske, Tiezheng Yu, Dan Su, Yan Xu, Etsuko Ishii, Ye Jin Bang, Andrea Madotto, and Pascale Fung. 2023. Survey of Hallucination in Natural Language Generation. *ACM Comput. Surv.* 55, 12, Article 248 (mar 2023), 38 pages. https://doi.org/10.1145/3571730

[42] Samia Kabir, David N. Udo-Imeh, Bonan Kou, and Tianyi Zhang. 2023. Who Answers It Better? An In-Depth Analysis of ChatGPT and Stack Overflow Answers to Software Engineering Questions. arXiv:2308.02312 [cs.SE]

[43] Daniel Kahneman. 2013. *Thinking, Fast and Slow.* Farrar, Straus and Giroux.

[44] Ryan Kennedy, Scott Clifford, Tyler Burleigh, Philip D. Waggoner, Ryan Jewell, and Nicholas J. G. Winter. 2020. The shape of and solutions to the MTurk quality crisis. *Political Science Research and Methods* 8, 4 (2020), 614–629. https://doi.org/10.1017/psrm.2020.6

[45] Sunnie S. Y. Kim, Nicole Meister, Vikram V. Ramaswamy, Ruth Fong, and Olga Russakovsky. 2022. HIVE: Evaluating the Human Interpretability of Visual Explanations. In *Computer Vision – ECCV 2022: 17th European Conference, Tel Aviv, Israel, October 23–27, 2022, Proceedings, Part XII* (Tel Aviv, Israel). Springer-Verlag, Berlin, Heidelberg, 280–298. https://doi.org/10.1007/978-3-031-19775-8_17

[46] Sunnie S. Y. Kim, Elizabeth Anne Watkins, Olga Russakovsky, Ruth Fong, and Andrés Monroy-Hernández. 2023. Humans, AI, and Context: Understanding End-Users' Trust in a Real-World Computer Vision Application. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency* (Chicago, IL, USA) *(FAccT '23)*. Association for Computing Machinery, New York, NY, USA, 77–88. https://doi.org/10.1145/3593013.3593978

[47] Lorenz Kuhn, Yarin Gal, and Sebastian Farquhar. 2023. Semantic Uncertainty: Linguistic Invariances for Uncertainty Estimation in Natural Language Generation. In *The Eleventh International Conference on Learning Representations*. https://openreview.net/forum?id=VD-AYtP0dve

[48] Vivian Lai, Chacha Chen, Alison Smith-Renner, Q. Vera Liao, and Chenhao Tan. 2023. Towards a Science of Human-AI Decision Making: An Overview of Design Space in Empirical Human-Subject Studies. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency (FAccT '23)*. Association for Computing Machinery, New York, NY, USA, 1369–1385. https://doi.org/10.1145/3593013.3594087

[49] Vivian Lai and Chenhao Tan. 2019. On Human Predictions with Explanations and Predictions of Machine Learning Models: A Case Study on Deception Detection. In *Proceedings of the Conference on Fairness, Accountability, and Transparency* (Atlanta, GA, USA) *(FAT* '19)*. Association for Computing Machinery, New York, NY, USA, 29–38. https://doi.org/10.1145/3287560.3287590

[50] Q. Vera Liao and Jennifer Wortman Vaughan. 2024. AI Transparency in the Age of LLMs: A Human-Centered Research Roadmap. *Harvard Data Science Review* (Feb 29 2024). https://hdsr.mitpress.mit.edu/pub/aelql9qy.

[51] Stephanie Lin, Jacob Hilton, and Owain Evans. 2022. Teaching Models to Express Their Uncertainty in Words. *Transactions on Machine Learning Research* (2022). https://openreview.net/forum?id=8s8K2UZGTZ

[52] Stephanie Lin, Jacob Hilton, and Owain Evans. 2022. TruthfulQA: Measuring How Models Mimic Human Falsehoods. In *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Association for Computational Linguistics, Dublin, Ireland, 3214–3252. https://doi.org/10.18653/v1/2022.acl-long.229

[53] Zhen Lin, Shubhendu Trivedi, and Jimeng Sun. 2023. Generating with Confidence: Uncertainty Quantification for Black-box Large Language Models. arXiv:2305.19187 [cs.CL]

[54] Dawn Liu, Marie Juanchich, Miroslav Sirota, and Sheina Orbell. 2020. The intuitive use of contextual information in decisions made with verbal and numerical quantifiers. *Quarterly Journal of Experimental Psychology* 73, 4 (2020), 481–494. https://doi.org/10.1177/1747021820903439 arXiv:https://doi.org/10.1177/1747021820903439 PMID: 31952448.

[55] Han Liu, Vivian Lai, and Chenhao Tan. 2021. Understanding the Effect of Out-of-distribution Examples and Interactive Explanations on Human-AI Decision Making. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW2, Article 408 (oct 2021), 45 pages. https://doi.org/10.1145/3479552

[56] Nelson Liu, Tianyi Zhang, and Percy Liang. 2023. Evaluating Verifiability in Generative Search Engines. In *Findings of the Association for Computational Linguistics: EMNLP 2023*, Houda Bouamor, Juan Pino, and Kalika Bali (Eds.). Association for Computational Linguistics, Singapore, 7001–7025. https://doi.org/10.18653/v1/2023.findings-emnlp.467

[57] Jennifer M. Logg. 2017. Theory of Machine: When Do People Rely on Algorithms? (2017). Harvard Business School NOM Unit Working Paper No. 17-086.

[58] Jennifer M. Logg, Julia A. Minson, and Don A. Moore. 2019. Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes* 151 (2019), 90–103.

[59] Alexandra Lorson, Chris Cummins, and Hannah Rohde. 2021. Strategic Use of (Un)certainty Expressions. *Frontiers in Communication* 6 (2021). https://doi.org/10.3389/fcomm.2021.635156

[60] Lu Lu, Nathan Neale, Nathaniel D. Line, and Mark Bonn. 2022. Improving Data Quality Using Amazon Mechanical Turk Through Platform Setup. *Cornell Hospitality Quarterly* 63, 2 (2022), 231–246. https://doi.org/10.1177/19389655211025475

[61] Zhuoran Lu and Ming Yin. 2021. Human Reliance on Machine Learning Models When Performance Feedback is Limited: Heuristics and Risks. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems (CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 78, 16 pages. https://doi.org/10.1145/3411764.3445562

[62] Catherine C. Marshall, Partha S.R. Goguladinne, Mudit Maheshwari, Apoorva Sathe, and Frank M. Shipman. 2023. Who Broke Amazon Mechanical Turk? An Analysis of Crowdsourcing Data Quality over Time. In *Proceedings of the 15th ACM Web Science Conference 2023* (Austin, TX, USA) *(WebSci '23)*. Association for Computing Machinery, New York, NY, USA, 335–345. https://doi.org/10.1145/3578503.3583622

[63] Winter Mason and Siddharth Suri. 2012. Conducting behavioral research on Amazon's Mechanical Turk. *Behavior Research Methods* 44, 1 (2012), 1–23. https://doi.org/10.3758/s13428-011-0124-6

[64] Roger C. Mayer, James H. Davis, and F. David Schoorman. 1995. An Integrative Model of Organizational Trust. *The Academy of Management Review* 20, 3 (1995), 709–734. http://www.jstor.org/stable/258792

[65] Joseph E McGrath. 1995. Methodology matters: Doing research in the behavioral and social sciences. In *Readings in Human–Computer Interaction*. Elsevier, 152–169.

[66] Yusuf Mehdi. 2023. The New Bing and Edge – Progress from Our First Month. https://blogs.bing.com/search/march_2023/The-New-Bing-and-Edge-%E2%80%93-Momentum-from-Our-First-Month

[67] Sabrina J. Mielke, Arthur Szlam, Emily Dinan, and Y-Lan Boureau. 2022. Reducing Conversational Agents' Overconfidence Through Linguistic Calibration. *Transactions of the Association for Computational Linguistics* 10 (2022), 857–872. https://doi.org/10.1162/tacl_a_00494

[68] Margaret Mitchell, Simone Wu, Andrew Zaldivar, Parker Barnes, Lucy Vasserman, Ben Hutchinson, Elena Spitzer, Inioluwa Deborah Raji, and Timnit Gebru. 2019. Model Cards for Model Reporting. In *Proceedings of the Conference on Fairness, Accountability, and Transparency* (Atlanta, GA, USA) *(FAT* '19)*. Association for Computing Machinery, New York, NY, USA, 220–229. https://doi.org/10.1145/3287560.3287596

[69] Sina Mohseni, Fan Yang, Shiva Pentyala, Mengnan Du, Yi Liu, Nic Lupfer, Xia Hu, Shuiwang Ji, and Eric Ragan. 2021. Machine Learning Explanations to Prevent Overtrust in Fake News Detection. *Proceedings of the International AAAI Conference on Web and Social Media* 15, 1 (May 2021), 421–431. https://doi.org/10.1609/icwsm.v15i1.18072

[70] Hussein Mozannar, Gagan Bansal, Adam Fourney, and Eric Horvitz. 2024. When to Show a Suggestion? Integrating Human Feedback in AI-Assisted Programming. *Proceedings of the AAAI Conference on Artificial Intelligence* 38, 9 (Mar. 2024), 10137–10144. https://doi.org/10.1609/aaai.v38i9.28878

[71] Clifford Nass and Youngme Moon. 2000. Machines and mindlessness: Social responses to computers. *Journal of social issues* 56, 1 (2000), 81–103.

[72] Demi Oba and Jonah A. Berger. 2022. How Hedges Impact Persuasion. https://doi.org/10.2139/ssrn.4170915

[73] OpenAI. 2023. GPT-4 Technical Report. arXiv:2303.08774 [cs.CL]

[74] Gabriele Paolacci and Jesse Chandler. 2014. Inside the Turk: Understanding Mechanical Turk as a Participant Pool. *Current Directions in Psychological Science* 23, 3 (2014), 184–188. https://doi.org/10.1177/0963721414531598

[75] European Parliament. 2024. European Union Artificial Intelligence Act Corrigendum. https://www.europarl.europa.eu/doceo/document/TA-9-2024-0138-FNL-COR01_EN.pdf

[76] Samir Passi and Mihaela Vorvoreanu. 2022. *Overreliance on AI: Literature Review*. Technical Report MSR-TR-2022-12. Microsoft. https://www.microsoft.com/en-us/research/publication/overreliance-on-ai-literature-review/

[77] Forough Poursabzi-Sangdeh, Daniel G Goldstein, Jake M Hofman, Jennifer Wortman Wortman Vaughan, and Hanna Wallach. 2021. Manipulating and Measuring Model Interpretability. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 237, 52 pages. https://doi.org/10.1145/3411764.3445315

[78] Snehal Prabhudesai, Leyao Yang, Sumit Asthana, Xun Huan, Q. Vera Liao, and Nikola Banovic. 2023. Understanding Uncertainty: How Lay Decision-Makers Perceive and Interpret Uncertainty in Human-AI Decision Making. In *Proceedings of the 28th International Conference on Intelligent User Interfaces* (Sydney, NSW, Australia) *(IUI '23)*. Association for Computing Machinery, New York, NY, USA, 379–396. https://doi.org/10.1145/3581641.3584033

[79] Rohith Pudari and Neil A. Ernst. 2023. From Copilot to Pilot: Towards AI Supported Software Development. arXiv:2303.04142 [cs.SE]

[80] Marissa Radensky, Julie Anne Séguin, Jang Soo Lim, Kristen Olson, and Robert Geiger. 2023. "I Think You Might Like This": Exploring Effects of Confidence Signal Patterns on Trust in and Reliance on Conversational Recommender Systems. In *Proceedings of the 2023 ACM Conference on Fairness, Accountability, and Transparency* (Chicago, IL, USA) *(FAccT '23)*. Association for Computing Machinery, New York, NY, USA, 792–804. https://doi.org/10.1145/3593013.3594043

[81] Max Schemmer, Niklas Kuehl, Carina Benz, Andrea Bartos, and Gerhard Satzger. 2023. Appropriate Reliance on AI Advice: Conceptualization and the Effect of Explanations. In *Proceedings of the 28th International Conference on Intelligent User Interfaces (IUI '23)*. Association for Computing Machinery, New York, NY, USA, 410–422. https://doi.org/10.1145/3581641.3584066

[82] Chirag Shah and Emily M. Bender. 2022. Situating Search. In *Proceedings of the 2022 Conference on Human Information Interaction and Retrieval* (Regensburg, Germany) *(CHIIR '22)*. Association for Computing Machinery, New York, NY, USA, 221–232. https://doi.org/10.1145/3498366.3505816

[83] Renee Shelby, Shalaleh Rismani, Kathryn Henne, AJung Moon, Negar Rostamzadeh, Paul Nicholas, N'Mah Yilla-Akbari, Jess Gallegos, Andrew Smart, Emilio Garcia, and Gurleen Virk. 2023. Sociotechnical Harms of Algorithmic Systems: Scoping a Taxonomy for Harm Reduction. In *Proceedings of the 2023 AAAI/ACM Conference on AI, Ethics, and Society (AIES '23)*. Association for Computing Machinery, New York, NY, USA, 723–741. https://doi.org/10.1145/3600211.3604673

[84] Sofia Eleni Spatharioti, David M. Rothschild, Daniel G. Goldstein, and Jake M. Hofman. 2023. Comparing Traditional and LLM-based Search for Consumer Choice: A Randomized Experiment. arXiv:2307.03744 [cs.HC]

[85] Mark Sullivan. 2023. Is Perplexity AI showing us the future of search? https://www.fastcompany.com/90883562/is-perplexity-ai-showing-us-the-future-of-search

[86] Cass R. Sunstein. 2002. Probability Neglect: Emotions, Worst Cases, and Law. *Yale Law Journal* 112, 61 (2002).

[87] Elham Tabassi. 2023. Artificial Intelligence Risk Management Framework (AI RMF 1.0). https://doi.org/10.6028/NIST.AI.100-1

[88] Katherine Tian, Eric Mitchell, Allan Zhou, Archit Sharma, Rafael Rafailov, Huaxiu Yao, Chelsea Finn, and Christopher Manning. 2023. Just Ask for Calibration: Strategies for Eliciting Calibrated Confidence Scores from Language Models Fine-Tuned with Human Feedback. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, Houda Bouamor, Juan Pino, and Kalika Bali (Eds.). Association for Computational Linguistics, Singapore, 5433–5442. https://doi.org/10.18653/v1/2023.emnlp-main.330

[89] Cristen Torrey, Susan R. Fussell, and Sara Kiesler. 2013. How a robot should give advice. In *2013 8th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*. 275–282. https://doi.org/10.1109/HRI.2013.6483599

[90] Takane Ueno, Yuto Sawa, Yeongdae Kim, Jacqueline Urakami, Hiroki Oura, and Katie Seaborn. 2022. Trust in Human-AI Interaction: Scoping Out Models, Measures, and Methods. In *Extended Abstracts of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI EA '22)*. Association for Computing Machinery, New York, NY, USA, Article 254, 7 pages. https://doi.org/10.1145/3491101.3519772

[91] Helena Vasconcelos, Gagan Bansal, Adam Fourney, Q. Vera Liao, and Jennifer Wortman Vaughan. 2023. Generation Probabilities Are Not Enough: Exploring the Effectiveness of Uncertainty Highlighting in AI-Powered Code Completions. arXiv:2302.07248 [cs.HC]

[92] Helena Vasconcelos, Matthew Jörke, Madeleine Grunde-McLaughlin, Tobias Gerstenberg, Michael S. Bernstein, and Ranjay Krishna. 2023. Explanations Can Reduce Overreliance on AI Systems During Decision-Making. *Proc. ACM Hum.-Comput. Interact.* 7, CSCW1, Article 129 (apr 2023), 38 pages. https://doi.org/10.1145/3579605

[93] Oleksandra Vereschak, Gilles Bailly, and Baptiste Caramiaux. 2021. How to Evaluate Trust in AI-Assisted Decision Making? A Survey of Empirical Methodologies. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW2, Article 327 (oct 2021), 39 pages. https://doi.org/10.1145/3476068

[94] Veniamin Veselovsky, Manoel Horta Ribeiro, and Robert West. 2023. Artificial Artificial Artificial Intelligence: Crowd Workers Widely Use Large Language Models for Text Production Tasks. arXiv:2306.07899 [cs.CL]

[95] H. Vogel, S. Appelbaum, H. Haller, and T. Ostermann. 2022. The Interpretation of Verbal Probabilities: A Systematic Literature Review and Meta-Analysis. *Studies in Health Technology and Informatics* 296 (17 Aug 2022), 9–16. https://doi.org/10.3233/SHTI220798

[96] Thomas S. Wallsten, David V. Budescu, Rami Zwick, and Steven M. Kemp. 1993. Preferences and reasons for communicating probabilistic information in verbal or numerical terms. *Bulletin of the psychonomic society* 31 (1993), 135–138. https://api.semanticscholar.org/CorpusID:145596140

[97] Xinru Wang and Ming Yin. 2021. Are explanations helpful? A comparative study of the effects of explanations in AI-assisted decision-making. In *26th International Conference on Intelligent User Interfaces*. 318–328.

[98] Margaret A. Webb and June P. Tangney. 0. Too Good to Be True: Bots and Bad Data From Mechanical Turk. *Perspectives on Psychological Science* 0, 0 (0), 17456916221120027. https://doi.org/10.1177/17456916221120027 PMID: 36343213.

[99] Laura Weidinger, Jonathan Uesato, Maribeth Rauh, Conor Griffin, Po-Sen Huang, John Mellor, Amelia Glaese, Myra Cheng, Borja Balle, Atoosa Kasirzadeh, Courtney Biles, Sasha Brown, Zac Kenton, Will Hawkins, Tom Stepleton, Abeba Birhane, Lisa Anne Hendricks, Laura Rimell, William Isaac, Julia Haas, Sean Legassick, Geoffrey Irving, and Iason Gabriel. 2022. Taxonomy of Risks Posed by Language Models. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency* (Seoul, Republic of Korea) *(FAccT '22)*. Association for Computing Machinery, New York, NY, USA, 214–229. https://doi.org/10.1145/3531146.3533088

[100] Benjamin Weiser and Nate Schweber. 2023. The ChatGPT Lawyer Explains Himself. *New York Times* (June 2023).

[101] Caroline J. Wesson and Briony D. Pulford. 2009. Verbal Expressions of Confidence and Doubt. *Psychological Reports* 105, 1 (2009), 151–160. https://doi.org/10.2466/PR0.105.1.151-160 PMID: 19810442.

[102] Paul D Windschitl and Gary L Wells. 1996. Measuring psychological uncertainty: Verbal versus numeric methods. *Journal of Experimental Psychology: Applied* 2, 4 (1996), 343–364. https://doi.org/10.1037/1076-898X.2.4.343

[103] Miao Xiong, Zhiyuan Hu, Xinyang Lu, YIFEI LI, Jie Fu, Junxian He, and Bryan Hooi. 2024. Can LLMs Express Their Uncertainty? An Empirical Evaluation of Confidence Elicitation in LLMs. In *The Twelfth International Conference on Learning Representations*. https://openreview.net/forum?id=gjeQKFxFpZ

[104] Ming Yin, Jennifer Wortman Vaughan, and Hanna Wallach. 2019. Understanding the Effect of Accuracy on Trust in Machine Learning Models. In *Proceedings of the 2019 ACM CHI Conference on Human Factors in Computing Systems*.

[105] Ann Yuan, Andy Coenen, Emily Reif, and Daphne Ippolito. 2022. Wordcraft: Story Writing With Large Language Models. In *27th International Conference on Intelligent User Interfaces* (Helsinki, Finland) *(IUI '22)*. Association for Computing Machinery, New York, NY, USA, 841–852. https://doi.org/10.1145/3490099.3511105

[106] Qiaoning Zhang, Matthew L Lee, and Scott Carter. 2022. You Complete Me: Human-AI Teams and Complementary Expertise. In *Proceedings of the 2022 CHI Conference on Human Factors in Computing Systems* (New Orleans, LA, USA) *(CHI '22)*. Association for Computing Machinery, New York, NY, USA, Article 114, 28 pages. https://doi.org/10.1145/3491102.3517791

[107] Yixuan Zhang, Joseph D Gaggiano, Nutchanon Yongsatianchot, Nurul M Suhaimi, Miso Kim, Yifan Sun, Jacqueline Griffin, and Andrea G Parker. 2023. What Do We Mean When We Talk about Trust in Social Media? A Systematic Review. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 670, 22 pages. https://doi.org/10.1145/3544548.3581019

[108] Yunfeng Zhang, Q Vera Liao, and Rachel KE Bellamy. 2020. Effect of confidence and explanation on accuracy and trust calibration in AI-assisted decision making. In *Proceedings of the 2020 conference on fairness, accountability, and transparency*. 295–305.

[109] Kaitlyn Zhou, Jena D. Hwang, Xiang Ren, and Maarten Sap. 2024. Relying on the Unreliable: The Impact of Language Models' Reluctance to Express Uncertainty. arXiv:2401.06730 [cs.CL]

[110] Kaitlyn Zhou, Dan Jurafsky, and Tatsunori Hashimoto. 2023. Navigating the Grey Area: How Expressions of Uncertainty and Overconfidence Affect Language Models. In *Proceedings of the 2023 Conference on Empirical Methods in Natural Language Processing*, Houda Bouamor, Juan Pino, and Kalika Bali (Eds.). Association for Computational Linguistics, Singapore, 5506–5524. https://doi.org/10.18653/v1/2023.emnlp-main.335

[111] Alf C. Zimmer. 1983. Verbal Vs. Numerical Processing of Subjective Probabilities. In *Decision Making Under Uncertainty*, Roland W. Scholz (Ed.). Advances in Psychology, Vol. 16. North-Holland, 159–182. https://doi.org/10.1016/S0166-4115(08)62198-6