The Calibration Gap between Model and Human Confidence in Large Language Models

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Abstract

For large language models (LLMs) to be trusted by humans they need to be well-calibrated in the sense that they can accurately assess and communicate how likely it is that their predictions are correct. Recent work has focused on the quality of internal LLM confidence assessments, but the question remains of how well LLMs can communicate this internal model confidence to human users. This paper explores the disparity between external human confidence in an LLM’s responses and the internal confidence of the model. Through experiments involving multiple-choice questions, we systematically examine human users’ ability to discern the reliability of LLM outputs. Our study focuses on two key areas: (1) assessing users’ perception of true LLM confidence and (2) investigating the impact of tailored explanations on this perception. The research highlights that default explanations from LLMs often lead to user overestimation of both the model’s confidence and its’ accuracy. By modifying the explanations to more accurately reflect the LLM’s internal confidence, we observe a significant shift in user perception, aligning it more closely with the model’s actual confidence levels. This adjustment in explanatory approach demonstrates potential for enhancing user trust and accuracy in assessing LLM outputs. The findings underscore the importance of transparent communication of confidence levels in LLMs, particularly in high-stakes applications where understanding the reliability of AI-generated information is essential.

Keywords:  Large Language Models, LLMs, Calibration, Trust, Explanations, User Confidence
1. Introduction

Large language models (LLMs) have markedly transformed how humans seek and consume information. LLMs are being deployed across diverse fields, including public health (Ali et al., 2023), coding (Zambrano et al., 2023), and education (Whalen et al. 2023). Despite their growing influence, LLMs are not without shortcomings. One notable issue is the possibility of generating responses that, while convincing, may be inaccurate or nonsensical. This phenomenon has been highlighted in several recent studies (Jo, 2023; Huang et al., 2023) and raises concerns about the reliability of these models. The unreliability of LLMs has led developers of LLMs to caution against uncritical acceptance of model outputs (OpenAI, 2022b), suggesting that it is not always clear when the models are or are not confident in the knowledge communicated to the user.

Recent research, however, indicates that LLMs have the ability, to a certain degree, to accurately discern their own knowledge boundaries. Large LLM models in particular can exhibit a reasonable level of calibration for multiple-choice questions such that the probability the model assigns to a selected answer tracks with the probability that this answer is correct (OpenAI, 2023; Kadavath et al. 2022; et al. 2023). In addition, recent studies show that LLMs can distinguish between answerable and unanswerable questions (Yin et al. 2023; Kadavath et al., 2022) and the internal state of an LLM can distinguish between truthful statements and lies (Azaria and Mitchell, 2023). These findings suggest that LLMs may possess an internal mechanism that is reflective of self-knowledge.

In the specific context of question-answering, an LLM’s model confidence is typically equated to the probability assigned by the LLM to the selected answer relative to other possible answers (e.g., (Jiang et al., 2021; Hendrycks et al., 2021)). However, from the perspective of a human interacting with the LLM, this internal model confidence is not usually displayed to human users as part of LLM output. Instead, in current practice, humans rely solely on the language produced by the LLM in order to assess LLM confidence. To contrast with model confidence, in this paper we use the term human confidence to refer to a human’s assessment (expressed as a probability) of how likely it is that the LLM’s answer is correct based only on the language produced by the LLM without any knowledge of the LLM’s internal model confidence.

Surprisingly, studies focused on investigating human confidence in LLM outputs are lacking. In this paper, we take a step in addressing this issue and investigate what we term the calibration gap, namely the difference in the reliability of (i) internal LLM model confidence and (ii) external human confidence. In effect, the calibration gap represents the gap between an LLM’s own internal confidence of what it knows and human perception of this confidence. We address two specific research questions in this context:

1. How Large is the Calibration Gap? i.e., is there a significant gap between LLM model confidence and human confidence, in terms of how each assesses the true accuracy of the LLM?

2. Can the Calibration Gap be Reduced? e.g., can the quality of human confidence in an LLM be improved by adapting the textual output of the LLM and by leveraging internal model confidence?
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Figure 1: Overview of the evaluation methodology for assessing the calibration gap between model confidence and human confidence in the model. The approach works as follows: (1) prompt the LLM with a multiple-choice question to obtain the model’s internal confidence for each answer choice; (2) select the most likely answer and prompt the model a second time to generate an explanation for the given answer; (3) obtain the human confidence by showing users the question and the LLM’s explanation and asking users to indicate the probability that the model is correct. In this toy example the model confidence is 0.46 for answer C, whereas the human confidence in 0.95

These questions have important implications for the design of reliable LLM assistants. Addressing the calibration gap is crucial for the development of effective and trustworthy assistants by aligning the LLM’s internal confidence with human perception of this confidence.

Our contributions in this context are twofold. First, we present a unique experimental study and dataset that directly captures human assessment of LLM confidence in a question-answering context, providing insight into human perceptions of LLM textual responses. Second, we test and suggest ways of generating LLM responses that improve the calibration quality of human confidence relative to the LLM assistant’s model confidence and the LLM’s true accuracy.

More specifically, as depicted in Figure 1, we use the well-known Massive Multitask Language Understanding (MMLU) dataset (Hendrycks et al., 2021) to conduct question-answering behavioral experiments where participants assess an LLM agent’s responses to multiple-choice questions. Participants estimate the accuracy of the LLM assistant, without any direct access to the LLM’s numerical model confidence, allowing us to make inferences about participants’ perceptions of the confidence of the LLM based on model explanations alone. Additionally, we conduct a series of experiments to prompt the LLM to generate explanations more aligned with its internal confidence.

The outline of the remainder of the paper is as follows. In Section 2, we review existing work on eliciting calibrated confidence scores from LLMs, psychology research on converting probabilities to verbal expressions of uncertainty, and human understanding of explanations. In Section 3, we describe our experimental setup for the behavioral experiments, and in Section 4, we discuss our findings and data analysis. Finally, we discuss key takeaways in Section 5.
2. Related Research

2.1 Eliciting LLM Confidence

Several approaches have been developed to elicit confidence in LLMs and to assess the degree to which the elicited confidence scores are calibrated (see (Geng et al., 2023) for an overview). One approach that is commonly used is to access internal model information such as token likelihoods, allowing for direct computation of relative probabilities of different possible answers in multiple-choice questions (Jiang et al., 2021; Kadavath et al., 2022; Xiao et al., 2022; Hendrycks et al., 2021; OpenAI, 2023). More recent research has focused on verbally expressing LLM model confidence such that the confidence is expressed in natural language as numeric strings (e.g., “80%”) (Lin et al., 2022; Xiong et al., 2023) or more qualitative expressions of confidence (e.g., “I am not confident the answer is X”) (Mielke et al., 2022; Zhou et al., 2023). To create calibrated verbal expressions of uncertainty, methods have included fine-tuning LLMs to produce verbalized probabilities for classes of math problems (Lin et al., 2022) and training models to connect the internal model representation to dialogue models that can translate internal probabilities to an appropriate linguistic expression of confidence (Mielke et al., 2022).

Methods that do not require access to internal model representations have used prompting strategies designed to elicit verbal expressions of uncertainty (Xiong et al., 2023; Zhou et al., 2023). Prompts that are designed to emphasize step-by-step reasoning about the correctness of individual steps and clarify the space of possible answers lead to better calibration than simple prompts that simply ask for a confidence rating (Xiong et al., 2023). For short-form question answering, prompting strategies can lead to calibrated confidence levels (Tian et al., 2023). However, for multiple-choice questions, which is the focus of our work, prompting approaches have been found to be less accurate compared to methods that read out model confidence (Xiong et al., 2023). Other black-box prompting methods for confidence elicitation have focused on the assessment of similarity among multiple responses from the model (Lin et al., 2023).

Our research builds on this prior work by integrating multiple approaches to eliciting confidence. We utilize a “white-box” method that reads out the internal token likelihoods. In addition, we use prompting strategies to verbally communicate the uncertainty expressed in the internal likelihoods to users. In contrast with prior work on LLM confidence elicitation, our goal is not to develop novel confidence elicitation procedures. Instead, the focus of our work is to assess the human perception of LLM uncertainty as expressed through explanations.

2.2 Human perception of verbal probability phrases

A significant body of psychology research has investigated perceptions of verbally expressed uncertainty across a wide range of domains, including climate policy, medicine, and intelligence forecasting (Budescu et al., 2014; Ho et al., 2015; Karelitz et al., 2002; Wallsten et al., 2008; O’Brien, 1989). These studies aim to understand how humans perceive verbal probability phrases such as “highly unlikely” and “almost certain” when describing the likelihood of an event occurring. The findings show that there are subjective differences in how people interpret linguistic probabilities (Dhami and Wallsten, 2005; Karelitz and Budescu, 2004).
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Wallsten et al., 2008) which has led to efforts to develop methods to reduce the subjectivity gap (Karelitz et al., 2002; Wallsten et al., 2008). Furthermore, the perceived range of probabilities varies between probability phrases. For example, “perhaps” is associated with a wide range of probabilities, whereas “almost no chance” is associated with less disagreement (O’Brien, 1989). Despite their lack of precision in communicating probabilities, verbal probability phrases provide a simple way to communicate uncertainty in natural language contexts. Our work expands on previous research by developing a mapping function that encourages the use of specific verbal probability phrases based on LLM’s model confidence.

More recently, the work by (Zhou et al., 2024) investigates how users behave in the presence of verbal phrases of uncertainty during human-LLM interactions. While their findings are consistent with ours, the two works use two different methodologies. (Zhou et al., 2024) craft templates using LLM-articulated expressions in a simulated trivia task and measures the users’ reliance on these expressions (regardless of model confidence). Conversely, our work uses actual LLM outputs and its confidence in an attempt to quantify the calibration gap. As a result, we are able to directly address the miscommunication of uncertainty from LLM to humans.

2.3 Effect of AI explanations on human decision-making

Much of the work examining the human perception and evaluation of machine-generated explanations has focused on machine learning classification models rather than LLMs (see (Rong et al., 2023) for an overview). These studies frequently employ feature highlighting to explain what areas of the image (Smith-Renner et al., 2020) or what fragments of documents (Feng and Boyd-Graber, 2019) can support the suggested classification. Studies have found mixed evidence for the effectiveness of these types of AI explanations in human decision-making (Steyvers and Kumar, 2023; Bansal et al., 2021; Bučinca et al. 2021; Wang and Yin, 2022). When humans are assisted by AI, adding AI explanations can improve human classification accuracy (Rong et al., 2023). However, many of these studies involved AI models that perform at a higher accuracy than humans, and therefore, these results suggest that the explanations simply increased reliance on the AI. In contrast to this prior work, our focus here is on human assessment of LLM confidence, i.e., the ability of people to tell when the LLMs answer is likely correct or incorrect based on the explanation provided, rather than on accuracy in decision-making.

3. Methodology

We used two publicly available state-of-the-art LLMs in our studies1: GPT-3.5 (OpenAI, 2022a) and PaLM2 (Anil et al., 2023). We apply both LLMs to a subset of multiple-choice questions from the MMLU data set (Hendrycks et al., 2021), as detailed in Section 3.1, and assess model confidence for each multiple-choice question. Model confidence enables us to investigate the relationship between model confidence and accuracy and to determine whether the LLM is reasonably well calibrated, independent of the LLM’s ability to elicit well-calibrated confidence from humans who use the LLM.

1. We also explored Llama2 70B and Llama-2-chat 70B but found the quality of the generated explanations to be unsatisfactory.
We conduct behavioral experiments (section 3.2), where the task for participants is to estimate the probability that the LLM model’s answer to a multiple-choice question is correct based on the explanation provided. We use the term human confidence to refer to this assessment about the LLM. In addition, with the assistance of the LLM, participants provide answers to the questions. Previous research has demonstrated that the MMLU multiple-choice questions are difficult for participants who lack domain expertise, resulting in near-chance accuracy (Hendrycks et al., 2021). We anticipate that these questions will be challenging to answer without the help of the LLM because the majority of the participants in our experiments lack domain expertise, and their perception of the explanation’s content will influence their assessment more than their own knowledge.

A key feature of the behavioral experiment is manipulating the language of uncertainty expressed in the explanations. Overall, we conducted three experiments using both types of LLMs:

• Experiment 1 assesses human perceptions of LLM accuracy based on default explanations generated by the LLM. We use standard prompts to elicit the answer and an explanation for the answer.

• Experiment 2 manipulates the prompts to produce three levels of uncertainty language (low, medium, and high confidence) and two levels of explanation length, resulting in six different types of explanations presented to participants. The prompts are designed to include uncertainty language corresponding to model confidence at the start of the explanation.

• Experiment 3 manipulates the prompts to change the default explanations from Experiment 1 according to three levels of uncertainty language. In contrast to Experiment 2, the explanations lead to more varied ways in which uncertainty language is expressed.

We use two types of metrics to evaluate the relationship between confidence (both human and model) and model accuracy as detailed in Section 3.3.

3.1 Question data set

The MMLU dataset is a comprehensive multitask dataset that contains multiple-choice questions from various knowledge domains, such as STEM, humanities, social sciences, and more (Hendrycks et al., 2021). In total, there are 14042 test set questions from 57 categories curated by undergraduate and graduate students from freely available online resources such as the GRE and USMLE. These questions range in difficulty from high-school to the professional level. The MMLU dataset is widely employed to measure a text model’s multitask accuracy, as it challenges models on their real-world text understanding beyond mere linguistic comprehension, thus making it a robust benchmark for model evaluation (Hendrycks et al., 2021; Hoffmann et al., 2023; Rae et al., 2021). For this project, we sampled a subset of the questions from a range of model’s confidence levels in selected categories from the full dataset to comprehensively evaluate people’s assessment of LLM model confidence.
3.1.1 Assessing uncertainty on multiple choice answers

Before sampling a subset of questions from the MMLU dataset, we first assessed the LLM model confidence of GPT-3.5 and PaLM2 language models to 14042 MMLU multiple-choice questions. This allowed us to then select questions with (somewhat) evenly distributed confidence levels. We followed the procedures described in the GPT-4 Technical Report (OpenAI, 2023) using a zero-shot prompting approach, in which the model was only prompted with the target question and its associated answer options. Figure 2 shows an example. We read out the log-probabilities for the top 5 tokens completed by the model using the APIs for the GPT3.5 (gpt-3.5-turbo-instruct) and the PaLM2 (text-bison@002) models\(^2\). The temperature parameter was set to 0. The answer was considered complete if the tokens included the single letters A, B, C, and D. The log scores were then converted and normalized to probabilities across the four answer options (so that the sum of the scores equaled one). Internal uncertainties, referred to in this paper as model confidence, were represented by these probabilities in all experiments, a common technique in calibration assessment with LLMs (Jiang et al., 2021; Kadavath et al., 2022; Xiao et al., 2022; Hendrycks et al., 2021. OpenAI, 2023).

A horizontal spring-block oscillator is in motion when a second block of equal mass falls on top of the oscillating block. If the two blocks stick together, what effect will this have on the amplitude of the oscillations?

Choose from the following options:
[A] It will increase the amplitude.
[B] It will decrease the amplitude.
[C] It will have no effect.
[D] It would depend on where the original block was in its cycle when the second block fell.

Please answer this question. Answer [A], [B], [C], or [D]. The answer therefore is: [ ]

Figure 2: Example prompt to elicit the answer and model confidence across answer options for a physics question from the MMLU dataset.

3.1.2 Sampling a subset of 350 questions

Based on the model confidence levels of each LLM for all MMLU questions, we created a subset separately for each LLM. In total, 35 questions were sampled for each of ten topics, for a total of 350 questions. For each topic, the 35 questions were sampled to approximately create a uniform distribution over model confidence using the confidence bins: 0.2-0.4, 0.4-0.6, 0.6-0.8, and 0.8-1.0. However, due to the small number of questions that lead to model confidence in the lowest confidence bin, fewer questions were sampled for the 0.2-0.4 confidence range. The Supplementary show the distribution over model confidence levels for the entire MMLU dataset as well as the question subset sampled for our study. Model accuracy across the 350 questions is 55% and 50% for GPT-3.5 and PaLM2, respectively.

\(^2\) The GPT3.5 model was accessed on Aug-Oct 2023 and PaLM2 model on January 2024.
3.2 Behavioral Experiments

This section describes the methodology we used in our behavioral experiments. Experiments 1, 2, and 3 differed only in the types of explanations presented to participants but otherwise followed the same general procedures as described below. Each experiment was conducted separately with the explanations from GPT-3.5 and PaLM2.

3.2.1 Participants

A total of 240 participants (40 in each experiment for each LLM) completed the study across Experiments 1, 2, and 3. Participants were native English speakers residing in the United States, recruited through Prolific (www.prolific.com). The University of California, Irvine Institutional Review Board (IRB) approved the experimental protocol. Participants who completed the study were paid $8 USD for their participation (approximately $12/hr). Prior to the experiment, participants were given detailed instructions outlining the experimental procedure as well as how to understand and interact with the user interface. Participants were asked to sign an integrity pledge after reading all of the instructions, stating that they would complete the experiment to the best of their abilities. After submitting their integrity pledge, participants were granted access to the experiment.

3.2.2 Experimental Procedure

Participants in all experiments were randomly assigned 40 multiple-choice questions from the pool of 350 MMLU questions. The questions were chosen in such a way that there would be four questions per topic. Furthermore, the sampling was balanced across model confidence bins (0.2-0.4, 0.4-0.6, 0.6-0.8, 0.8-1.0). This sampling procedure ensured that all participants were given an equal number of questions from each topic and were exposed to questions at all levels of difficulty for each topic.

Furthermore, in Experiments 2 and 3, we balanced the types of explanation styles across questions so that each question was presented approximately the same number of times with each style. It should be noted that for each subject, each question was presented only once, and each question received only one explanation style. The counterbalancing, on the other hand, ensured that the same question had (roughly) an equal number of observations for each explanation style (across participants).

The participant’s task was divided into two phases for each question, as shown in Figure 3. In the first stage, participants had to provide a probability estimate that the LLM’s answer was correct. In the second phase, participants must answer the question with the assistance of the LLM. Participants were instructed to use their own knowledge as well as the LLM’s response when making their own answer selection for this phase.

At the end of the experiments, we administered a brief survey in which participants self-assessed their knowledge of the ten topics. Participants were asked to estimate the expected accuracy for each topic if they were presented with questions similar to those they encountered during the experiment.
3.2.3 Creating explanation styles with varying degrees of uncertainty

This section describes how we constructed prompts to elicit explanations with varying levels of uncertainty language in the experiments. For additional details on the exact prompts used, see Appendix Table 3. Table 1 contains examples of explanations from the three experiments and styles.

**Experiment 1: baseline explanations** To generate the baseline explanations for Experiment 1, we used a simple prompt that asked for an explanation, which would also repeat the answer.

**Experiment 2: modified explanations** We used prompts that were designed to change the explanations to express three different levels of confidence. The low, medium, and high confidence prompts instructed the LLM to “mention you are” *not sure/somewhat sure/sure* in the explanation for each of the low, medium, and high confidence prompts, respectively. The prompts elicited responses in which the beginning of each explanation indicated the level of uncertainty (e.g., “I am not sure the answer is [B] because” for the low confidence prompt). Furthermore, the prompts led to additional differences in explanations for why the LLM lacked confidence (e.g., “further research may be required to confirm this,” “it is not possible to definitively state that...”). Experiment 2 also varied the length of the explanation. We created a shorter variant for each of the three types of explanations by adding an instruction to use as few words as possible in the explanation. The average length of the long and short explanations was 770 and 227 characters, respectively, for GPT-3.5, and 441 and 123 characters, respectively for PaLM2. In total, Experiment 2 included six types of explanations (three levels of uncertainty x two levels of length).

**Experiment 3: modified explanations** We used three different types of prompts to elicit low/medium and high-confidence explanations and did not include a length manip-
ulation. In this approach, we gave the LLM the baseline explanation from Experiment 1 in the prompt and instructed the LLM to “rewrite the explanation as if you are” not sure/somewhat sure/sure for each of the three confidence levels.

Table 1: Example explanations given by GPT-3.5 for the different prompts used in the experiments. The particular question is: Which of the following is incorrectly named? A) CaCl2 calcium chloride; B) Fe(NO3)3 iron(III) nitrate; C) AlBr3 aluminum tribromide; D) K2Cr2O7 potassium dichromate

<table>
<thead>
<tr>
<th>Prompt Style</th>
<th>Explanation</th>
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<tbody>
<tr>
<td><strong>Experiment 1</strong></td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>The answer is [B] because the correct name for Fe(NO3)3 is iron(III) nitrate, not iron(II) nitrate. The Roman numeral in parentheses after the metal name indicates the oxidation state of the metal ion in the compound, and in this case, it should be III (3) instead of II (2). Therefore, the compound is incorrectly named as iron(II) nitrate.</td>
</tr>
<tr>
<td><strong>Experiment 2</strong></td>
<td></td>
</tr>
<tr>
<td>Low Confidence &amp; Long</td>
<td>I am not sure that the answer is [B] because iron(III) nitrate is a correct name for Fe(NO3)3. Iron(III) refers to the oxidation state of iron in the compound, which is +3, and nitrate is the anion present. However, I am not completely confident in my answer because it is possible that there is another, more specific name for this compound that I am not aware of.</td>
</tr>
<tr>
<td>Medium Confidence &amp; Long</td>
<td>I am somewhat sure that the answer is [B] because iron(III) nitrate should be named iron(III) nitrite. This is because the nitrate ion has a charge of -1, while the nitrite ion has a charge of -2. Therefore, the correct formula for iron(III) nitrite should be Fe(NO2)3. Since the formula given in option [B] does not match the correct formula, I am somewhat sure that this option is incorrectly named.</td>
</tr>
<tr>
<td>High Confidence &amp; Long</td>
<td>I am sure that the answer is [B] because the correct name for Fe(NO3)3 is iron(III) nitrate, not iron(II) nitrate. The Roman numeral in parentheses after the metal name indicates the charge of the metal ion in the compound. In this case, iron has a charge of +3, not +2. Therefore, the correct name for Fe(NO3)3 is iron(III) nitrate, making [B] incorrectly named.</td>
</tr>
<tr>
<td>Low Confidence &amp; Short</td>
<td>I am not sure if the answer is [B] because iron(III) nitrate is the correct name for Fe(NO3)3.</td>
</tr>
<tr>
<td>Medium Confidence &amp; Short</td>
<td>I am somewhat sure that the answer is [B] because the correct name for Fe(NO3)3 is iron(III) nitrate, not iron(II) nitrate.</td>
</tr>
<tr>
<td>High Confidence &amp; Short</td>
<td>I am sure that the answer is [B] because iron(III) nitrate should be written as Fe(NO3)3, not Fe3(NO3)3.</td>
</tr>
<tr>
<td><strong>Experiment 3</strong></td>
<td></td>
</tr>
<tr>
<td>Low Confidence</td>
<td>I am not entirely certain, but I believe the answer is [B]. The reason for this is that the compound Fe(NO3)3 is typically named as iron(III) nitrate, not iron(II) nitrate. The Roman numeral in parentheses after the metal name indicates the oxidation state of the metal ion in the compound, and in this case, it should be III (3) instead of II (2). Therefore, it is possible that the compound is incorrectly named as iron(II) nitrate.</td>
</tr>
<tr>
<td>Medium Confidence</td>
<td>I believe the answer is [B] because the compound Fe(NO3)3 is incorrectly named as iron(II) nitrate. The correct name should be iron(III) nitrate, as indicated by the Roman numeral III (3) after the metal name. However, I am not completely confident in my answer and would appreciate further clarification or confirmation.</td>
</tr>
<tr>
<td>High Confidence</td>
<td>The answer is [B] because the compound Fe(NO3)3 is incorrectly named as iron(II) nitrate. The correct name for this compound is iron(III) nitrate, as indicated by the Roman numeral III after the metal name. This indicates that the iron ion has an oxidation state of 3, not 2. Therefore, the compound is incorrectly named and the correct name is iron(III) nitrate.</td>
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3.2.4 Generating explanations modified by model confidence

In experiments 2 and 3 we use the following simple approach to automatically select the type of explanation on the basis of LLM model confidence, in order to better align human confidence with LLM accuracy. We use a simple decision rule that selects the type of explanation \( s \in \{\text{low confidence, medium confidence, high confidence}\} \) based on the LLM model confidence score \( p \):

\[
s = \begin{cases} 
\text{low confidence} & \text{if } p \leq \theta_1 \\
\text{medium confidence} & \text{if } \theta_1 < p \leq \theta_2 \\
\text{high confidence} & \text{if } \theta_2 < p 
\end{cases}
\] (1)

The parameters \( \theta_1 \) and \( \theta_2 \) determine the ranges where low, medium, and high confidence explanations are chosen. The application of this rule to a given parameter setting leads
to any participant estimates being filtered out if the explanation style used for a specific question does not match the selected style. This allowed us to simulate the effect of participants receiving different types of explanations based on model confidence (i.e., lower confidence explanations for low model confidence and high confidence explanations for high model confidence). The Appendix provides details on the optimization procedure and also a demonstration that the results are not particularly sensitive to the parameter settings.

3.3 Metrics

To investigate the relationship between the accuracy of answers to multiple-choice questions and the confidence (either human confidence or model confidence) associated with them, we utilize a range of metrics to evaluate this association. The primary focus is on understanding how well confidence levels correlate with the correctness of answers. To achieve this, we use both Expected Calibration Error (ECE) and the Area under the Curve (AUC) metric. These metrics assess the extent of overconfidence in predictions as well as the diagnostic effectiveness of confidence scores in distinguishing between correct and incorrect answers (Xiong et al., 2023; Tian et al., 2023; Jiang et al., 2021; Kadavath et al., 2022; Xiao et al., 2022). The use of AUC in this context parallels various metrics in psychology for metacognitive discrimination or sensitivity, which similarly aim to evaluate the effectiveness of confidence scores in distinguishing between correct and incorrect answers (Fleming and Lau, 2014). In addition, in the Supplementary, we also show results for the additional metric of Overconfidence Error (OE).

3.3.1 Expected Calibration Error (ECE)

We evaluate miscalibration using the Expected Calibration Error (ECE), as detailed in (Guo et al., 2017; Naeini et al., 2015). ECE is calculated by averaging the absolute differences between accuracy and confidence across \( M \) equal-width probability bins:

\[
ECE = \frac{1}{N} \sum_{m=1}^{M} \left| \frac{B_m}{N} \right| \left| \text{conf}(B_m) - \text{acc}(B_m) \right| \tag{2}
\]

where \( N \) represents the total sample count, \( B_m \) the \( m \)th confidence bin, and \( \text{acc}(B_m) \) and \( \text{conf}(B_m) \) denote the accuracy and average confidence for samples in the \( m \)th bin. ECE does not account for the direction of deviations between accuracy and confidence per bin respectively, so a nonzero ECE can indicate a mix of over- and underconfidence. While recent work (Kumar et al., 2019; Gruber and Buettner, 2022) has shown that ECE can under-estimate the true calibration error, the potential for under-estimation should not be a significant issue given that we are interested in analyzing differences in ECE rather than unbiased estimates of the error itself.

3.3.2 Area under the Curve (AUC)

The AUC metric is employed to assess the diagnostic ability of confidence scores in distinguishing between correct and incorrect answers. Utilizing the Mann-Whitney U statistic approach, the AUC represents the probability that a randomly chosen correct answer has a higher confidence score compared to a randomly chosen incorrect answer:
AUC = \frac{1}{N_{pos} \times N_{neg}} \sum_{i=1}^{N_{pos}} \sum_{j=1}^{N_{neg}} I(C_i > C_j) \tag{3}

In this equation, \( N_{pos} \) and \( N_{neg} \) denote the counts of correct (positive) and incorrect (negative) answers, respectively. \( C_i \) and \( C_j \) represent the confidence scores of the \( i \)th and \( j \)th correct and incorrect answers, respectively. \( I \) is an indicator function, which equals 1 if \( C_i > C_j \) and 0 otherwise. This method evaluates each pair of correct and incorrect answers to determine if the confidence score for the correct answer surpasses that of the incorrect one. The AUC is then the fraction of these pairs satisfying this criterion, measuring the capability of confidence scores to differentiate between correct and incorrect responses, with AUC values ranging from 0.5 (indicating no better than chance discrimination) to 1 (signifying perfect discrimination).

3.4 Statistical Analysis

To assess statistical significance, we utilize Bayes factors (BFs) to determine the extent to which the observed data adjust our belief in the alternative and null hypotheses. Values of 3 < BF < 10 and BF > 10 indicate moderate and strong evidence against the null hypothesis, respectively. Similarly, values of 1/10 < BF < 1/3 and BF < 1/10 indicate moderate and strong evidence in favor of the null hypothesis, respectively. We report Bayes factors for Bayesian t-tests using the default priors as recommended by (Rouder et al., 2012).

4. Results

4.1 Modified explanations affect human confidence

We first assess if the linguistic manipulations in Experiments 2 and 3, which systematically modify the LLMs explanations to better reflect model confidence, have a direct effect on human confidence as measured in our experiments. Figure 4 shows that the type of uncertainty language used in the explanations has a strong influence on human confidence in Experiments 2 and 3. When the explanations contain less certain language (“I am not sure”, “not confident”, “I think”, “not confident in this explanation”), participants are less confident that the answer is correct. For comparison, the mean confidence in Experiment 1 for the unmodified explanations was 0.77 and 0.75 for GPT-3.5 and PaLM2 respectively. In contrast, the low confidence (“not sure”) explanations in Experiment 2 led to significantly lower confidence with means of 0.52 and 0.48 for GPT-3.5 and PaLM2 respectively (BF > 100 for both LLMs). The results overall confirm that people can appropriately interpret verbal cues about uncertainty.

For GPT-3.5, the length of the explanation generally did not affect the confidence in the answers (BF < 1 for all three comparisons of short and long explanations across explanation styles). However, for PaLM2, for the least confident explanations, longer explanations received higher confidence than shorter explanations (BF > 100). In the results for Experiment 2 in the remainder of the paper we analyze the results collapsed over the short and long explanations.
Figure 4: Distribution of human confidence across explanation styles in Experiments 1, 2, and 3. For reference, dashed lines show the average human confidence for the unmodified explanations in Experiment 1. The error bars represent the 95% confidence interval across questions.

4.2 Calibration and discrimination

4.2.1 Calibration and discrimination gaps

We next analyze the results of comparing human and model confidence for the case where LLMs generate default explanations for participants (Experiment 1) compared to where the explanations are modified to reflect model confidence (Experiments 2 and 3). The results show that there is a significant gap between what LLMs know and what humans think they know on the basis of these explanations.

Figure 5 shows the Expected Calibration Error (ECE) and the Area Under the Curve (AUC) for both model and human confidence (for the full results with an additional metric for overconfidence, see the Appendix). Focusing first on calibration (left panel), the results show a significant calibration gap; for both LLMs, the ECE metric is significantly lower for model confidence (in gray) than for human confidence with baseline explanations (in blue). This gap demonstrates that standard explanations provided by the LLM do not enable participants to judge the likelihood of correctness of the LLM's answers, leading to a misalignment between perceived accuracy and actual LLM accuracy.

Furthermore, there is also a gap between how well model and human confidence discriminate between correct and incorrect answers (Figure 5, right panel). Whereas the LLM model confidence discriminates between correct and incorrect answers well above chance (GPT-3.5 AUC=.751, PaLM2 AUC=0.746), the participants who view the default explanations in Experiment 1 were only slightly better than random guessing with AUC values of 0.589 and 0.602 for GPT-3.5 and PaLM2 explanations respectively.
Figure 5: Calibration gap between model and human confidence. The plots show the calibration error (assessed by ECE; lower is better), and discrimination (assessed by AUC; higher is better) of model and human confidence across LLMs and experiments. Vertical dashed lines represent the calibration and discrimination gap between human confidence for unmodified explanations and model confidence. The AUC values were computed separately for each participant with error bars representing the 95% confidence interval. Because of data sparsity, the ECE values were computed at the group level.

Figure 5 also shows the results from Experiments 2 and 3 after the LLM explanations have been modified to reflect model confidence. The results in Figure 5 (left panel, green and pink bars) show that the calibration gap has narrowed substantially. While there is still generally a higher calibration error for human confidence relative to model confidence, the calibration gap has decreased significantly for both LLMs relative to the baseline explanations in Experiment 1. Furthermore, Figure 5 (right panel) shows that the discrimination gap (as measured by AUC) has also been narrowed relative to the baseline explanations for both LLMs (BF > 10 for both Experiments 2 and 3).

Overall, these results show that selecting the type of explanation based on LLM model confidence leads to improved calibration and discrimination performance, where human confidence in the LLM is more closely related to the actual accuracy of the LLM.

4.2.2 Reliability diagrams across experiments and LLMs

Figure 6 expands on the calibration results in Figure 5 to show detailed calibration results for each LLM and each experimental condition. The diagrams show how well model confidence (left column) and human confidence (right three columns) are calibrated. The ideal calibration (i.e., ECE=0) would yield results along the diagonal. Both LLMs and humans have a tendency to be overconfident, resulting in calibration lines below the diagonal. However, human overconfidence when presented with the default explanations is greater, indicating that people generally believe the LLMs are more accurate than they actually are. The histograms (inset panels) demonstrate that a significant portion of the calibration error
is due to participants’ propensity to produce high confidence scores, even though the model accuracy for the associated questions is much lower than expected based on confidence.

4.3 Accuracy

4.3.1 Participants lack specialized knowledge

For the experiments with GPT-3.5, participants’ average answer accuracy was 50%, closely aligning with LLM’s 52% accuracy rate. Similarly, for the experiments with PaLM2, average participant accuracy was 46%, similar to the 50% accuracy rate for the LLM. Across all experiments and LLMs, for a majority (82%) of responses, participants chose the answer that agreed with the answer in the explanation provided by the LLM. When participants chose to alter the answer, the average accuracy was 32% which is lower than the LLM’s accuracy of 45% for these particular questions. These findings suggest limited success in participants’ ability to accurately answer the questions independent of the LLM’s explanation. This is consistent with findings from Hendrycks et al., 2021, showing that Mechanical Turk workers without specialized knowledge (akin to our participant pool) scored 35% accuracy on similar questions.

4.3.2 Self-assessed expertise does not affect performance

At the end of the experiment, participants estimated the performance they would achieve on similar questions for each of the 10 topics. The median of these self-assessed expertise estimates did not substantially vary between topics: from 30% (e.g., high school physics)
The Calibration Gap between Model and Human Confidence

to 45% (e.g., high school world history). Examining the impact of perceived expertise on accuracy estimation, we divided participants into two groups based on whether their self-rated expertise was above or below 50% separately for each of the 10 topics. For the experiments with GPT-3.5, the higher expertise groups generally had better discrimination (AUC 0.573 vs. AUC 0.538), but there was no evidence that this difference was significant (BF < 1). In addition, the calibration error was comparable between the two groups (ECE = .261 vs. .257). Similarly, no effect of expertise was found for the experiments with PaLM2. Therefore, participants who considered themselves more knowledgeable about a topic were not more adept at estimating GPT’s performance in that area.

5. Discussion

The core of our research centered on bridging the gap between what an LLM knows and what users perceive it knows. This gap is critical, as the reliance on LLMs for decision-making processes in various domains is rapidly increasing. Several studies have examined LLM confidence for multiple choice questions (Kadavath et al., 2022; OpenAI, 2023; Hendrycks et al., 2021; Xiong et al., 2023) and assessing the reliability of LLM explanations in this context (Tanneru et al., 2023), but there has been little research to investigate user confidence in LLM output. Our results showed that users consistently overestimated how accurate LLM outputs were, especially when they relied on the models’ default explanations. This was true for two different LLMs. This tendency towards overconfidence in LLM capabilities is a significant concern, especially in scenarios where critical decisions are based on LLM information. The inability of users to discern the reliability of LLM responses not only undermines the utility of these models but also poses risks in situations where user understanding of model accuracy is critical.

A key contribution of this research lies in demonstrating the effectiveness of tailored explanations in bridging this perception gap. This was achieved by altering the prompts used to generate explanations based on model confidence, thereby controlling the expression of uncertainty within the responses. Specifically, we designed these prompts to induce varying degrees of certainty in the explanations, ranging from expressions of low confidence (e.g., ”I am not sure the answer is [B] because”) to high confidence (e.g., ”I am confident the answer is [B] because”). By modifying the language of the LLM’s responses to better reflect model confidence, users showed improved calibration in their assessment of the LLM’s reliability and were better able to discriminate between correct and incorrect answers. This improvement underscores the importance of transparent communication from LLMs, suggesting a need for researchers to investigate how model explanations affect user perception.

One limitation of the current study is the focus on a specific type of question (multiple-choice) and the assessment of a single dataset (MMLU). The extent to which these results apply to other types of questions and datasets remains an open question. Further research could investigate the applicability of our findings across a broader range of scenarios, as well as the challenge of calibrating human perception in response to open-ended questions. Another limitation of this study is that our approach to modifying the prompt based on internal uncertainty required the LLM to be prompted twice: once to read out the answer and model confidence, and again to produce an explanation modified by the model confi-
The Calibration Gap between Model and Human Confidence

dence. Future research could investigate how to produce confidence-modified explanations in a single step.

In conclusion, our research highlights the critical role of clear and accurate communication in the interaction between users and LLMs. Enhancing the alignment between model confidence and the user’s perception of model confidence can lead to a more responsible and trustworthy use of LLMs, particularly in areas where the accuracy of AI-generated information is critical.

Acknowledgments

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Kaitlyn Zhou, Jena D. Hwang, Xiang Ren, and Maarten Sap. Relying on the unreliable: The impact of language models’ reluctance to express uncertainty, 2024.
Appendix A. Additional Results

Table 2 shows the full set of results across experiments and LLMs. The table also includes results for an additional performance metric, the Overconfidence Error (OE). The metric is an adaptation of the ECE formula, specifically focusing on cases of overconfidence Thulasidasan et al. (2019):

$$OE = \sum_{m=1}^{M} \frac{|B_m|}{N} \left[ conf(B_m) \times \max(0, conf(B_m) - acc(B_m)) \right]$$

This penalizes predictions by the weight of the confidence but only when confidence exceeds accuracy.

Table 2: Expected Calibration error (ECE), Overconfidence Error (OE), and Area under the Curve (AUC) of model and human confidence across experiments.

<table>
<thead>
<tr>
<th>LLM</th>
<th>Confidence Score</th>
<th>ECE</th>
<th>OE</th>
<th>AUC</th>
</tr>
</thead>
<tbody>
<tr>
<td>GPT-3.5</td>
<td>model confidence</td>
<td>.104</td>
<td>.064</td>
<td>.751</td>
</tr>
<tr>
<td></td>
<td>human confidence: experiment 1, default explanations</td>
<td>.264</td>
<td>.220</td>
<td>.589</td>
</tr>
<tr>
<td></td>
<td>human confidence: experiment 2, modified explanations</td>
<td>.183</td>
<td>.145</td>
<td>.692</td>
</tr>
<tr>
<td></td>
<td>human confidence: experiment 3, modified explanations</td>
<td>.158</td>
<td>.121</td>
<td>.678</td>
</tr>
<tr>
<td>PaLM2</td>
<td>model confidence</td>
<td>.154</td>
<td>.098</td>
<td>.746</td>
</tr>
<tr>
<td></td>
<td>human confidence: experiment 1, default explanations</td>
<td>.291</td>
<td>.229</td>
<td>.602</td>
</tr>
<tr>
<td></td>
<td>human confidence: experiment 2, modified explanations</td>
<td>.134</td>
<td>.078</td>
<td>.655</td>
</tr>
<tr>
<td></td>
<td>human confidence: experiment 3, modified explanations</td>
<td>.195</td>
<td>.155</td>
<td>.689</td>
</tr>
</tbody>
</table>

Appendix B. Additional Model Confidence Results

Figure 7 shows the calibration diagrams for the full set of 14,042 test questions from the MMLU dataset. For GPT-3.5, the accuracy across all questions is 63% with an AUC of 0.78. When computing model confidence, 8.7% of the answers were incomplete and were removed from consideration. For PaLM2, the accuracy is 51% with an AUC of 0.73. For comparison, Figure 8 shows the calibration diagrams for the subset of 350 questions used for the behavioral experiments.

Furthermore, we confirmed that we could replicate the GPT-4 Technical Report’s OpenAI (2023) five-shot results. Five-shot prompting with GPT-3.5 (detailed in Appendix 8 of the report) resulted in 71% accuracy (compared to 70% reported in Table 2 of the report). The zero-shot approach is the focus of this paper. The zero-shot approach simplifies the construction of explanations, and our goal is not to maximize language model accuracy.
Appendix C. Optimization Procedure

To apply the selection rule, we reduced Experiment 2’s six explanation styles to three. Therefore, for both Experiment 2 and 3, the selection rule considered a choice of one of three explanation styles for each question (i.e., low, medium, and high confidence explanations).

The parameters $\theta_1$ and $\theta_2$ were chosen to optimize a combination of the ECE and AUC score (weighting the ECE by 33% relative to AUC). The optimization was performed separately for Experiments 2 and 3 and the two LLMs. The parameters were optimized using a basic grid search with values ranging from 0.25 to 1, with the constraint that $\theta_1 < \theta_2$. For GPT-3.5, Experiment 2’s optimized parameters were $\theta_1 = 0.55$ and $\theta_2 = 0.65$, while Experiment 3’s optimized parameters were $\theta_1 = 0.75$ and $\theta_2 = 0.95$. For PaLM2, Experiment 2’s optimized parameters were $\theta_1 = 0.80$ and $\theta_2 = 0.85$, while Experiment 3’s optimized parameters were $\theta_1 = 0.70$ and $\theta_2 = 0.75$.

C.1 Sensitivity Analysis

The calibration and discrimination results are not overly sensitive to parameter changes. The resulting AUC and ECE outcomes for each parameter setting are shown in Figures 9 and 10. For example, for GPT-3.5, Experiment 2 yields mean AUC and ECE values of 0.631 and 0.217 across all parameter settings, which are higher than the results of Experiment 1. Furthermore, there is moderate evidence (BF$_{63}$) for an improved AUC for 41% of parameter
Figure 8: Calibration diagram for GPT-3.5 and PaLM2 model for subset of 350 questions of MMLU questions used for behavioral experiments. Note that the lower count of questions in the lowest confidence bin is due to the sparsity of questions in that confidence bin.

combinations. The parameter settings in Experiment 3 had more selective effects. There was only moderate evidence (BF ≥ 3) for an improved AUC for 17% of parameter settings. The smaller effects of the explanation styles in Experiment 3 presumably made the performance results more dependent on the specific selection rule.

Appendix D. Prompt Styles Across Experiments
Figure 9: Sensitivity analysis for Experiment 2. Results show the effect of different thresholds ($\theta_1, \theta_2$) to select explanation styles. Top and bottom panels show the resulting AUC and ECE that relate the human confidence to the actual accuracy of the LLM.
Figure 10: Sensitivity analysis for Experiment 3. Results show the effect of different thresholds ($\theta_1$, $\theta_2$) to select explanation styles. Top and bottom panels show the resulting AUC and ECE that relate the human confidence to the actual accuracy of the LLM.
Table 3: Prompt styles across experiments

<table>
<thead>
<tr>
<th>Experiment Style</th>
<th>Prompt</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Baseline</strong></td>
<td>Problem: [question] Choose from the following options: [A] Option A [B] Option B [C] Option C [D] Option D. The answer you give is: [answer]. Provide an explanation for the answer you gave. In your explanation, you must include the answer.</td>
</tr>
<tr>
<td><strong>Experiment 2</strong></td>
<td></td>
</tr>
<tr>
<td>Low Confidence &amp; Long</td>
<td>Problem: [question] Choose from the following options: [A] Option A [B] Option B [C] Option C [D] Option D. The answer you give is: [answer]. Write an explanation why you are not sure that the answer is [answer]. In your explanation, mention that you are not sure and include the answer. Start with 'I am:'.</td>
</tr>
<tr>
<td>Medium Confidence &amp; Long</td>
<td>Problem: [question] Choose from the following options: [A] Option A [B] Option B [C] Option C [D] Option D. The answer you give is: [answer]. Write an explanation why you somewhat sure that the answer is [answer]. In your explanation, mention that you are somewhat sure and include the answer. Start with 'I am:'.</td>
</tr>
<tr>
<td>High Confidence &amp; Long</td>
<td>Problem: [question] Choose from the following options: [A] Option A [B] Option B [C] Option C [D] Option D. The answer you give is: [answer]. Write an explanation why you are sure that the answer is [answer]. In your explanation, mention that you are sure and include the answer. Use as few words as possible. Start with 'I am:'.</td>
</tr>
<tr>
<td>Low Confidence &amp; Short</td>
<td>Problem: [question] Choose from the following options: [A] Option A [B] Option B [C] Option C [D] Option D. The answer you give is: [answer]. Write a very short explanation why you are not sure that the answer is [answer]. In your explanation, mention that you are not sure and include the answer. Use as few words as possible. Start with 'I am:'.</td>
</tr>
<tr>
<td>Medium Confidence &amp; Short</td>
<td>Problem: [question] Choose from the following options: [A] Option A [B] Option B [C] Option C [D] Option D. The answer you give is: [answer]. Write a very short explanation why you somewhat sure that the answer is [answer]. In your explanation, mention that you are somewhat sure and include the answer. Use as few words as possible. Start with 'I am:'.</td>
</tr>
<tr>
<td>High Confidence &amp; Short</td>
<td>Problem: [question] Choose from the following options: [A] Option A [B] Option B [C] Option C [D] Option D. The answer you give is: [answer]. Write a very short explanation why you are sure that the answer is [answer]. In your explanation, mention that you are sure and include the answer. Use as few words as possible. Start with 'I am:'.</td>
</tr>
<tr>
<td><strong>Experiment 3</strong></td>
<td></td>
</tr>
<tr>
<td>Low Confidence</td>
<td>Problem: [question] Choose from the following options: [A] Option A [B] Option B [C] Option C [D] Option D. The answer you give is: [answer]. The explanation you give is: [baseline explanation]. Rewrite the explanation as if you are not sure and ensure that you include language or phrases that conveys your complete lack of confidence. In your explanation, you must include the answer.</td>
</tr>
<tr>
<td>Medium Confidence</td>
<td>Problem: [question] Choose from the following options: [A] Option A [B] Option B [C] Option C [D] Option D. The answer you give is: [answer]. The explanation you give is: [baseline explanation]. Rewrite the explanation as if you are somewhat sure and ensure that you include language or phrases that conveys your lack of confidence. In your explanation, you must include the answer.</td>
</tr>
<tr>
<td>High Confidence</td>
<td>Problem: [question] Choose from the following options: [A] Option A [B] Option B [C] Option C [D] Option D. The answer you give is: [answer]. The explanation you give is: [baseline explanation]. Rewrite the explanation as if you are very sure and ensure that you include language or phrases that conveys your confidence. In your explanation, you must include the answer.</td>
</tr>
</tbody>
</table>