

Human Evaluation of Spoken vs. Visual Explanations for Open-Domain QA

Ana Valeria González^{*1}, Gagan Bansal², Angela Fan^{3,4}, Yashar Mehdad³, Robin Jia³, and Srinivasan Iyer³

¹University of Copenhagen, ²University of Washington, ³Facebook AI, ⁴LORIA
ana@di.ku.dk
bansalg@cs.washington.edu
{angelafan, mehdad, robinjia, sviyer}@fb.com

Abstract

While research on explaining predictions of open-domain QA systems (ODQA) to users is gaining momentum, most works have failed to evaluate the extent to which explanations improve user trust. While few works evaluate explanations using user studies, they employ settings that may deviate from the end-user’s usage in-the-wild: ODQA is most ubiquitous in *voice*-assistants, yet current research only evaluates explanations using a *visual* display, and may erroneously extrapolate conclusions about the most performant explanations to other modalities. To alleviate these issues, we conduct user studies that measure whether explanations help users correctly decide when to accept or reject an ODQA system’s answer. Unlike prior work, we control for explanation *modality*, *i.e.*, whether they are communicated to users through a spoken or visual interface, and contrast effectiveness across modalities. Our results show that explanations derived from retrieved evidence passages can outperform strong baselines (calibrated confidence) across modalities but the best explanation strategy in fact changes with the modality. We show common failure cases of current explanations, emphasize end-to-end evaluation of explanations, and caution against evaluating them in proxy modalities that are different from deployment.

1 Introduction

Despite copious interest in developing explainable AI and NLP, there is increasing skepticism about whether explanations of system predictions provide value to users in many important downstream applications. For instance, for classifying sentiment and answering LSAT questions, Bansal et al. (2020) observed that textual explanations were no more helpful to users for decision-making than simply presenting model confidence. Similarly, Chu et al.

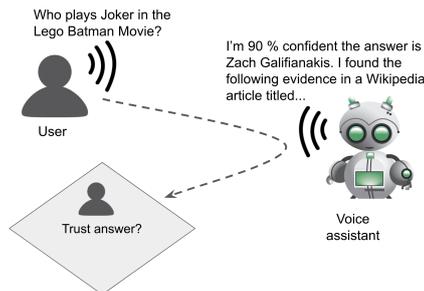


Figure 1: Using end-to-end user studies, we evaluate whether explanation strategies of open-domain question answering assistants help users decide when to trust (or reject) predicted answers.

(2020) observed that visual explanations fail to significantly improve human accuracy or trust. Such negative results present a cautionary tale for explainable NLP and emphasize the need to evaluate explanations using well-designed user-studies.

In this work, we explore this problem for *Open-Domain Question Answering* models, which are increasingly deployed in voice-assistant and Web search to answer users’ questions. In ODQA, users ask factoid questions (*e.g.*, “Who plays the Joker in the Lego Batman movie?”) and the system answers from a large corpus of documents (*e.g.*, Wikipedia). Even though the accuracy of such systems is rapidly improving, deployed models are imperfect and can make mistakes, pointing towards a need to provide users with mechanisms (*e.g.*, displaying uncertainty) that aid in *appropriate reliance* on these systems. This motivates one of our key research questions, *Does explaining the system’s reasoning, help users better assess when to (dis)trust their predictions?* We henceforth refer to a user’s ability to distinguish correct and incorrect answers as *error-detectability*.

Recent work conducted user studies and concluded that explanations improve error-detectability for ODQA (Lamm et al., 2020; Feng and Boyd-Graber, 2019a). Lamm et al. (2020)

* Work done while at Facebook AI.

showed that providing an evidence sentence as well as coreference and entailment information, improves error-detectability marginally. However, this study lacked a strong baseline that uses calibrated confidence and which on other domains has been shown to be effective. While [Feng and Boyd-Graber \(2019a\)](#) did present model confidence along with highlighting of important attributes, and influential training examples, their evaluation setup is only suitable for visual displays.

In practice, ODQA systems are ubiquitous in voice assistants, with recent surveys indicating that voice is an increasingly popular method for asking questions on a smartphone.¹ Spoken language interfaces can also improve accessibility of technology for people with visual impairments and reading disabilities. Explanations in the spoken modality pose unique challenges—information will impose different cognitive demands depending on whether it is shown visually or by voice ([Sweller, 2011](#); [Leahy and Sweller, 2016](#)), which could make long explanations less effective in the spoken modality.

We focus on two central questions: (1) Do explanations help users discriminate between correct and incorrect model predictions across both spoken and visual modalities? and (2) Do the preferred explanation strategies depend on modality? We present the first study comparing both visual and spoken explanations for ODQA on error-detectability, involving over 500 participants, and evaluate three types of natural language explanations: a retrieved evidence paragraph, a retrieved evidence sentence, and a human-written sentence that abstractively summarizes the evidence.

Our findings indicate that while natural language explanations help users in both modalities, they can mislead users into accepting incorrect predictions. Additionally, users prefer different explanation types in different modalities. In the spoken modality, all explanation types outperform the strong baseline of presenting calibrated confidence scores, demonstrating that they are helpful to users. Among the three explanation types, extractive sentence explanations are the most useful. On the other hand, extractive explanations and human-written abstractive explanations frequently mislead users into trusting incorrect answers. In contrast, longer extractive explanations are more effective than sentence-length explanations in the vi-

sual modality, which demonstrates the importance of tailoring explanations to the user interface.

2 Related Work

Natural Language Explanations Recent work has introduced neural models that are trained to perform a task and output a natural language (NL) explanation. [Camburu et al. \(2018\)](#) and [Rajani et al. \(2019\)](#), both introduce methods for training self-explaining models using free-form NL explanations collected from crowdsourced workers for natural language inference and common sense reasoning. [Atanasova et al. \(2020\)](#) introduce a method for generating explanations for fact verification using human veracity justifications. [Lei et al. \(2016\)](#) introduced an approach for extracting *rationales* by selecting phrases from the input text which are sufficient to provide an output. Rationales have since been introduced for various NLP tasks ([DeYoung et al., 2020](#); [Chen et al., 2018](#); [Yang et al., 2018](#)).

[Lamm et al. \(2020\)](#) introduce QED explanations in ODQA consisting of the sentence containing the answer, coreference and entailment information. However, unlike free-form explanations or rationales, these explanations are too complex to adapt to the spoken modality. In question answering, many current models provide an answer and a rationale (or *extractive* evidence). We evaluate extractive evidences from a state-of-the-art ODQA model, along with human-written summaries.

Evaluating Explanations The quality of NL explanations has previously been evaluated using automatic metrics that measure the agreement of explanations with human annotations ([DeYoung et al., 2020](#); [Paranjape et al., 2020](#); [Swanson et al., 2020](#); [Camburu et al., 2018](#); [Rajani et al., 2019](#)). It is not clear how these metrics reflect the usefulness of explanations in practice. As the goal of explainability is to make model decisions more predictable to *human* end users, a more useful way of evaluating explanations is through human evaluation.

Some human evaluations have used proxy tasks to evaluate explanations ([Hase and Bansal, 2020](#); [Nguyen, 2018](#)), however, [Buçinca et al. \(2020\)](#) showed that both subjective measures and proxy tasks tend to be misleading and do not reflect results in actual decision making tasks.

Within question answering, [Feng and Boyd-Graber \(2019b\)](#) evaluate how expert and novice trivia players engage with explanations. [Lamm et al. \(2020\)](#) evaluate how QED explanations help

¹<https://www.perficient.com/insights/research-hub/voice-usage-trends>

raters determine whether a model decision is correct or incorrect, and find marginal improvements on rater accuracy. Unlike these works, we simplify the presentation setup so that we can adapt explanations across different modalities. Bansal et al. (2020) observed that for sentiment analysis and answering LSAT questions, state-of-the-art explanation methods are not better than revealing model confidence scores and they increase the likelihood of users accepting wrong model predictions. We compare confidence to various explanation strategies for ODQA, but unlike previous work, we use *calibrated* model confidence.

Open-domain QA ODQA consists of answering questions from a corpus of unstructured documents². Currently, ODQA models consist of two components: (1) a document *retriever* which finds the most relevant documents from a large collection and (2) a machine comprehension model or *reader* component, which selects the answer within the chosen documents (Chen et al., 2017; Das et al., 2018; Lee et al., 2019a; Karpukhin et al., 2020). Recent work focuses on identifying answers in Wikipedia (Karpukhin et al., 2020) as well as the web (Joshi et al., 2017), encompassing both short extractive answers (Rajpurkar et al., 2016) and long explanatory answers (Fan et al., 2019).

3 Visual vs. Spoken Modalities

When presenting NL explanations to users, we must keep in mind that users typically process information differently across the spoken and visual modalities. In this section we discuss work in learning and psychology research, which point to the differences motivating our evaluation.

1. **Real-time processing:** Flowerdew et al. (1994) observe that one of the main differences in how people process spoken versus written information is linearity. When listening, as opposed to reading, information progresses without you. Readers, on the other hand, are able to go back and dwell on specific points in the text, skip over and jump back and forth (Buck, 1991; Lund, 1991). Although in some scenarios it is possible to get spoken information repeated, it may not be as effective as re-reading (see below).

²<https://trec.nist.gov/data/qamain.html>

2. **Recall of information:** People tend to recall less after listening versus reading (Osada, 2004). Lund (1991) found that for some listeners, listening to information again was not as effective as re-reading. While advanced listeners benefited from listening multiple times, this was a controlled learning scenario simulating students learning classroom material; we would expect users in an ODQA setting to be slightly more passive.
3. **Effect on concentration:** The heavier cognitive load imposed by listening to information can make people lose concentration more easily. Thompson and Rubin (1996) found that optimal length for listening materials was around 30 seconds to 2 minutes. Beyond that, listeners would lose full concentration. When people interact with voice assistants they may be on the go, or may be surrounded by additional distractions not present in a learning environment. This in turn may make the optimal length of material (explanations, in our case) much shorter.

We argue that these differences in processing of spoken and written information can have tremendous consequences in the effectiveness of natural language explanations in ODQA. Our experimental setup is the first to address these differences.

4 Experimental Setup

We design our user study to evaluate explanation effectiveness for ODQA by varying two factors: *type* of explanation and *modality* of communication. We combine variations of each factor to obtain explanation conditions (Section 4.1) and obtain them using a state-of-the-art ODQA model (Section 4.3). We then deploy these conditions as HITs on Amazon Mechanical Turk (MTurk) to validate five hypotheses, each stating relative effectiveness of conditions at improving error-detectability (Section 4.2). Since MTurk studies can be prone to noise, to ensure quality-control, we make and justify various design choices (Section 4.4).

4.1 Explanation Types and Conditions

ODQA models can justify their predictions by pointing to *evidence* text containing the predicted answer (Das et al., 2018; Lee et al., 2019a; Karpukhin et al., 2020). We experiment with two types of *extractive* explanations:

- **EXTRACTIVE-SENT**: Extracts and communicates a sentence containing the predicted answer as evidence.
- **EXTRACTIVE-LONG**: Extracts and communicates a longer, multi-sentence paragraph containing the answer as evidence.

While extractive explanations are simpler to generate, we also evaluate a third explanation type that has potential to more succinctly communicate evidence spread across documents (Liu et al., 2019).

- **ABSTRACTIVE**: Generates and communicates a new text snippet to justify the predicted answer.

Final explanation conditions For the *voice modality*, we test five conditions, two baselines and three explanation types: (1) **BASELINE**: present only the top answer, (2) **CONFIDENCE**, a second, stronger baseline that presents the top answer along with the model’s uncertainty in prediction, (3) **ABSTRACTIVE**, (4) **EXTRACTIVE-LONG**, and (5) **EXTRACTIVE-SENT**.

In the *visual modality*, we have 2 conditions corresponding to the **EXTRACTIVE-LONG** and **EXTRACTIVE-SENT** explanation types. Here, we were primarily interested in contrasting these with the voice modality. Examples of our explanations can be found in Appendix A.

4.2 Hypotheses

We investigated five (pre-registered) hypothesis about the relative performance of various explanation conditions at improving error-detectability, motivated by pilot studies and authors’ intuitions.

- **H1**: Presenting model confidence will improve performance over the baseline.
- **H2**: *Spoken* **EXTRACTIVE-SENT** explanations will perform better than **CONFIDENCE** — the explanation would provide additional context to help validate predicted answers.
- **H3**: *Spoken* **EXTRACTIVE-SENT** will perform better than *Spoken* **EXTRACTIVE-LONG**. Since the spoken modality may impose higher cognitive limitations on people (Section 3), users may find concise explanations more useful despite them providing less context.

- **H4**: **ABSTRACTIVE** will help users discriminate between correct and incorrect more than **CONFIDENCE** alone.

Abstractive summaries may contain more relevant information than extractive explanations of the same length, which may help users make better decisions.

- **H5**: *Visual* **EXTRACTIVE-LONG** will perform better than *spoken* **EXTRACTIVE-LONG**.

4.3 Implementation Details for Conditions

Dataset For training our model and obtaining test questions for our user study, we used questions, answers, and documents from the Natural Questions (NQ) corpus (Kwiatkowski et al., 2019). NQ is composed of anonymized queries posed by real users on the Google search engine, and the answers are human-annotated spans in Wikipedia articles. The *naturally occurring* aspect of this data makes it a more realistic task for evaluating explanations. To simplify the study, we restrict our attention to the subset of questions with short answers (< 6 tokens) following Lee et al. (2019b). This subset contains 80k training examples, 8,757 examples for development, and 3,610 examples for testing.

Model We train the current (extractive) state-of-the-art model on NQ: Dense Passage Retrieval and Reader (DPR) (Karpukhin et al., 2020). Similar to Karpukhin et al. (2020), we split documents (entire Wikipedia articles), into shorter passages of equal lengths (100 tokens). To answer an input question, DPR uses two separate *dense* encoders $E_Q(\cdot)$ and $E_P(\cdot)$ to encode the question and all passages in the corpus into vectors. It then retrieves k most similar passages, where *passage similarity* to a question is defined using a dot product: $sim(q, p) = E_Q(q)^\top E_P(p)$.

Given the top k passages, a neural reader (Section 2) assigns a passage selection score to each passage, and a *span score* to every answer span. The original model uses the best span from the passage with the highest passage selection score as the final answer. However, we re-score each answer using the product of the passage and span score and use the highest-scored answer as the prediction. Our initial analysis showed that this re-scoring improved exact match scores of predicted answers.

Generating explanations To create our extractive explanations, we use the passage associated

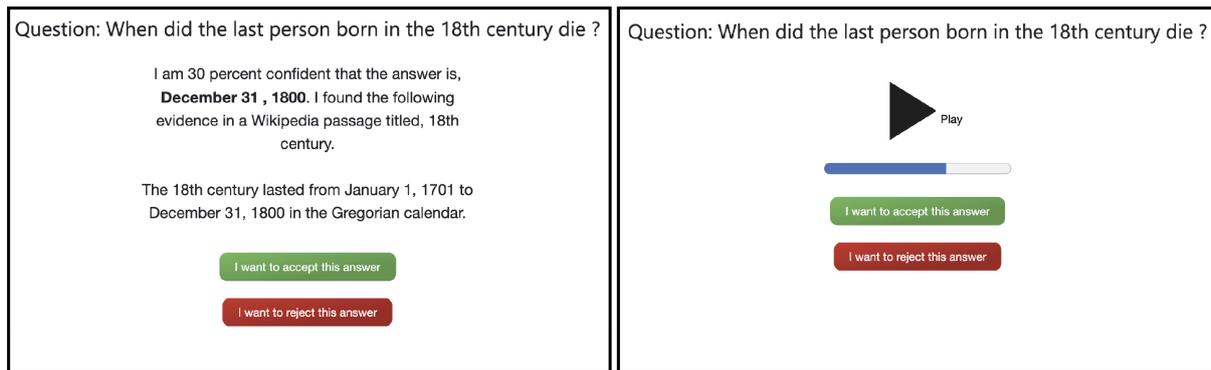


Figure 2: UI for visual (left) and spoken modalities (right) for EXTRACTIVE-SENT explanation type. Users either read or hear an explanation and decide whether to trust or discard the QA system’s prediction.

with DPR’s answer— EXTRACTIVE-SENT is defined as the single sentence in the passage containing the answer and EXTRACTIVE-LONG is defined as the entire passage. Since DPR does not generate abstractive explanations, we simulate ABSTRACTIVE by manually creating a single sentence that captures the main information of EXTRACTIVE-SENT and adds additional relevant information from EXTRACTIVE-LONG, whilst remaining the same length as EXTRACTIVE-SENT.

In order to improve transparency, in addition to presenting the evidence text in each explanation condition, we also inform users that the source of the text is Wikipedia and provide them with the *title* of the article containing the passage together with the model’s (calibrated) uncertainty in its prediction. Figure 2 shows an example of the final EXTRACTIVE-SENT explanation condition. To convert text to speech, we use an internally-available TTS tool. For the questions we used in our study, when spoken, our final ABSTRACTIVE and EXTRACTIVE-SENT conditions were on average 15 seconds long, EXTRACTIVE-LONG was between 30-40 seconds.

Confidence calibration Confidence scores generated by neural networks (*e.g.*, by normalizing softmax scores) often suffer from poor calibration (Guo et al. (2017)). To alleviate this issue and to follow best practices (Amershi et al., 2019) for creating strong baselines, we calibrate our ODQA model’s confidence using *temperature scaling* (Guo et al., 2017), which is a *post hoc* calibration algorithm suitable for multi-class problems. We calibrate the top 10 outputs of the model. We defer details on the improvement in calibration obtained through temperature scaling, and its implementation, to Appendix B.

4.4 User study & Interface

We conduct our experiments using Amazon Mechanical Turk. Our task presents each worker with 40 questions one-by-one, while showing them the model’s answer (along with other condition-dependant information, such as confidence or explanation) and asks them to either *accept* the model’s prediction if they think it is correct or *reject* it otherwise. Figure 2 shows an example. For each of the 7 conditions we hire 75 workers.

Additional details about our setting and the instructions can be found in Appendix D.

Question selection We deliberately sample a set of questions on which the model’s aggregate (exact-match) accuracy is 50%; thus any improvements in error-detectability, beyond random-performance, must be a result of users making optimal assessment about the model’s correctness. To improve generalization of results, we average results over three such mutually exclusive sets of 40 questions. Before sampling the questions we also removed questions that were ambiguous or questions where the model was indeed correct but the explanations failed to justify the answer. For brevity, we defer these details and justifications of these details to the Appendix C.

Incentive scheme To encourage MTurk workers to engage and pay attention to the task, we used a bonus-based strategy — When users accept a correct answer, we give them a 15 cent bonus but when they accept an incorrect answer they lose the same amount³. This choice aims to simulate real-world cost and utility from interacting successfully

³If participants ended up with a negative bonus, no deductions were made from their base pay, instead their bonus was simply zero

(or unsuccessfully) with AI assistants (Bansal et al., 2019). Table 4.4 shows the final pay-off matrix that we used.

PREDICTION/DECISION	ACCEPT	REJECT
CORRECT	+\$0.15	\$0
INCORRECT	-\$0.15	\$0

Table 1: MTurk worker’s bonus as a function of the correctness of ODQA model’s prediction and the user’s decision to accept or reject the predicted answer.

Post-task survey After the main task, we asked participants to (1) rate the length of responses, (2) rate their helpfulness and (3) give us general feedback on what worked and how explanations could be made better. For the *spoken modality*, we also asked participants to rate the clarity of the voice to understand if confusion originated from text-to-speech challenges. The survey as presented to the participants can be found in Appendix E.

Quantitative measures of error-detectability

We quantify user performance at error-detectability using the following five metrics:

- **Accuracy:** Percentage of times a user accepts correct and rejects incorrect answers. A high accuracy indicates high error-detectability.
- **Cumulative reward:** The total dollar reward in bonuses earned by a worker based on the payoff in Table 4.4. Note that, unlike accuracy, the payoff matrix is not symmetric wrt. user decision and correctness of predictions.
- **% Accepts | correct:** Percentage of times the user accepts *correct* answers. If a setting yields a *high* true positive rate, this would indicate this setting helps users better recognize correct model responses.
- **% Accepts | incorrect:** Percentage of times the user accepts *incorrect* answers. For this metric, *lower* is better. If a setting yields a high number, this would indicate that this setting misleads users more often.
- **Time:** The median time taken by a user to reach a decision after a question is shown.

When computing these metrics, we remove the first 4 questions for each worker to account for

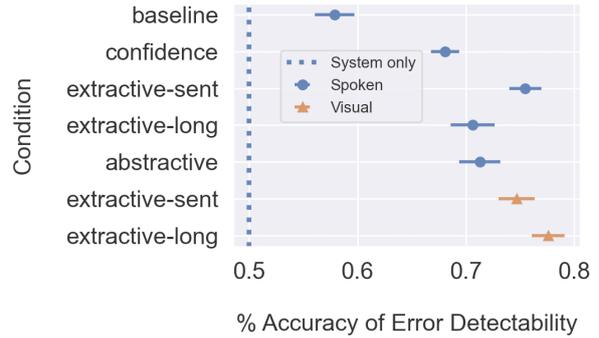


Figure 3: Accuracy of users at error-detectability (75 workers per condition). In the *spoken modality*, EXTRACTIVE-SENT explanations yield the best results and is significantly better than CONFIDENCE. In contrast, in the *visual modality*, EXTRACTIVE-LONG explanations perform best. We observe a statistically significant ($p < 0.01$) difference between EXTRACTIVE-LONG in visual versus spoken, perhaps because of differences in user’s cognitive limitations across modalities.

workers getting used to the interface. We pre-registered this procedure prior to running our final studies and, as a result, the maximum cumulative reward for this setup is \$ 2.70.

5 Results

To validate our hypothesis (Section 4.2) we compare explanation methods on the quantitative metrics (Section 5.1). To further understand participant behavior we analyze responses to the post-task survey (Section 5.2), and analyze common cases where explanations misled the users (Section 5.3). Results for reward and time metrics are included in Appendix F.1 and F.2.

5.1 Quantitative Results

Figure 3 shows average user accuracy at error-detectability with 75 workers per condition. Similarly to Lamm et al. (2020), in order to validate hypotheses and compute statistical significance, we fit a generalized linear mixed effects model using the `lme4` library in R and the formula $a \sim c + (1|w) + (1|q)$, where a is accuracy, c is the condition, w is the worker id and q is the question id. We run pairwise comparisons of these effects using Holm-Bonferroni to correct for multiple hypothesis testing. For both the spoken and visual modalities, all conditions lead to significantly higher accuracies than BASELINE ($p < 0.01$).

Model confidence improved accuracy of error-detectability In Figure 3, CONFIDENCE achieves higher accuracy than BASELINE— 68.1% vs. 57.2%. This difference was statistically significant ($p < 0.01$), thus validating **H1**. While previous guidelines recommend displaying confidence to users (Amershi et al., 2019) and show its benefit for sentiment classification and LSAT (Bansal et al., 2020), our observations provide the first empirical evidence that confidence serves as a simple yet stronger baseline against which explanations for ODQA should be compared.

Explaining via an evidence sentence further improved performance. The more interesting comparisons are between explanation types and CONFIDENCE. In both modalities, EXTRACTIVE-SENT performed better than CONFIDENCE. For example, in the *spoken modality*, EXTRACTIVE-SENT improved accuracy over CONFIDENCE from 68.1% to 75.6% ($p < 0.01$); thus validating **H2**. Contrary to recent prior works that observed no benefit from explaining predictions, this result provides and confirms a concrete application of explanations where they help users in an end-to-end task.

While longer explanations improved performance over more concise explanations in the visual modality, they worsened performance in the spoken modality. Figure 3 shows that, for the visual modality, EXTRACTIVE-LONG outperforms EXTRACTIVE-SENT explanations in the visual modality— 77.6% vs. 74.7% ($p < 0.4$). Conversely, for spoken, EXTRACTIVE-SENT is better than EXTRACTIVE-LONG— 75.6% vs. 70.4% ($p < 0.01$); thus supporting **H3**. In fact, the decrease was severe enough that we no longer observed a statistically significant difference between long explanations and simply communicating confidence ($p = 0.9$).

Although communicating the same content, *visual* EXTRACTIVE-LONG led to significantly better accuracy than their spoken version— 77.6% vs. 70.4% ($p < 0.01$); thus validating **H5**. These results indicate large differences, across modalities, in user ability to process and utilize explanations, and how these differences need to be accounted for while evaluating and developing explanations.

Despite improving conciseness, abstractive summaries (of the longer explanations) did not help improve performance in the spoken modality. Figure 3 shows that while ABSTRACTIVE per-

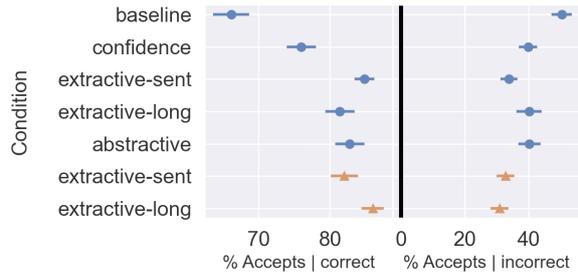


Figure 4: (Left) Explanations significantly increased participant ability to detect *correct* answers compared to simply displaying confidence. (Right) However, only EXTRACTIVE-SENT in the spoken modality and both explanations in the visual modality decreased the rate at which users are misled.

forms marginally better than confidence— 71.3% vs. 68.1%, the difference is not statistically significant ($p = 0.4$) and thus we could not validate **H4**. This result indicates that the length of the explanation (*e.g.*, number of tokens) is not the only factor that affects user performance, instead the density of information also increases cognitive load on users. This finding is in line with the Time Based Resource Sharing (TBRS) model (Barrouillet et al., 2007), a theory on working memory establishing that time as well as the complexity of what is being communicated, both play a role in cognitive demand. We also observe the same effect in users subjective rating of length of explanation (Section 5.2).

All explanations significantly increased participants’ ability to detect correct answers, but only some explanations improved their ability to detect incorrect answers. Instead of aggregate accuracy, Figure 4 splits and visualizes how often users accept correct and incorrect answers. For accepting *correct* model predictions, all *visual* and *spoken* explanation conditions significantly helped compared to CONFIDENCE (at least $p < 0.05$).

In terms of accepting incorrect predictions, in the *spoken modality*, only EXTRACTIVE-SENT is significantly better (*i.e.*, lower) than CONFIDENCE— 34% vs. 40% ($p < 0.05$). Whereas in the *visual modality*, both EXTRACTIVE-LONG and EXTRACTIVE-SENT lead to improvements over CONFIDENCE— 30% ($p < 0.01$) and 32% ($p < 0.05$), respectively. This shows that although explanations decrease the chance of being misled by the system, the least misleading explanations change with modality.

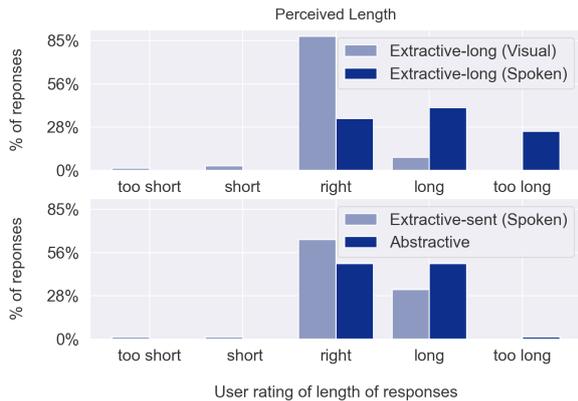


Figure 5: **Top:** Users perceive the same explanation to be longer in the spoken modality. **Bottom:** While EXTRACTIVE-SENT and ABSTRACTIVE were the same length, participants rate the latter as longer more often perhaps because of they contain more content.

5.2 Qualitative results

We analyzed user responses to the post-task survey to understand their experience, what helped them and how the system could serve them better.

Voice clarity To verify that the quality of the text-to-speech tool that we employed did not negatively affect our experiments, we asked users to rate the clarity of the assistant’s voice as *very poor*, *poor*, *fair*, *good*, or *excellent*. More than 90% of participants felt that the voice was good or excellent.

Length preference We asked participants to rate the length of the explanation as *too short*, *short*, *right*, *long*, or *too-long*. For EXTRACTIVE-LONG, over 85% of workers perceived that in the *visual modality*, responses were the right length. On the other hand, in the *spoken modality*, nearly 65% of participants felt that the responses were too long. In both modalities, users were presented with the same explanations, hence their lengths were exactly the same. This result indicates that what works well in one modality *cannot* simply be transferred as is to another modality.

Additionally, even though ABSTRACTIVE and EXTRACTIVE-SENT were the same duration, in the post experimental survey, users indicated more often that they found ABSTRACTIVE to be long, as opposed to EXTRACTIVE-SENT. As previously mentioned, this relates to the TBRS model of working memory (Barrouillet et al., 2007). We hypothesize that *our* ABSTRACTIVE explanations, which integrate more information than EXTRACTIVE-SENT in the same amount of time, might be more taxing

in the working memory, making them less effective and in turn making users perceive them as being longer. These results are shown in Figure 5.

Perceived helpfulness Participants were asked whether the responses helped them in their decision making. Their responses showed that CONFIDENCE and all explanation conditions were perceived as helpful by at least 80% of participants, with no real differences among them except for EXTRACTIVE-LONG in the visual modality (which is perceived helpful by close to 90% of users). Interestingly, 50% of participants indicated BASELINE to be helpful. In contrast, our results in Figure 3 show that different explanations actually differ in their eventual helpfulness. These results suggest that subjective measures can sometimes correlate with actual performance when the differences are large, but for the most-part and smaller differences, the result from subjective rating can be unreliable. These findings align with prior observation made (Buçinca et al., 2020) that showed that evaluating explanations on proxy metrics can lead to incorrect conclusions. More on our these findings are shown in Figure 9 in Appendix F.4.

User feedback In order to get more specific details about how to improve the presentation of information, we asked participants at the end of the survey: *Do you have any additional feedback on what the system can improve?* Two annotators read through about 400 responses across all conditions, and created codes to capture possible areas of improvement. The annotators then used these codes to classify responses. Many users gave feedback that was not insightful (e.g. "can’t think of anything to improve"). After removing such responses, 175 responses remained for the final analysis. We computed the inter-annotator agreement using Cohen’s k ($k=0.74$). Here we briefly describe the most interesting findings, with more details about the codes we used and additional results in Appendix F.5.

In BASELINE, where the answer was provided with no additional information, about 50% of **participants mentioned that they would have liked it if the voice changed with system certainty**. In CONFIDENCE, around 30% of participants give this feedback as well. Interestingly, for explanation conditions, this feedback is not seen as often.

For EXTRACTIVE-SENT in both modalities, EXTRACTIVE-LONG in the visual modality and ABSTRACTIVE, 10-35 % of **participants would**

like the level of detail to adapt to the model certainty. More specifically, users would like to have more details or additional answers *only* when the model is not confident in the prediction. This strategy seems similar to *adaptive explanations* proposed by (Bansal et al., 2020).

For the EXTRACTIVE-LONG condition in the *spoken modality* the feedback was mostly about the length of the responses. 78% of participants mentioned that responses should be shorter, which aligns with the higher perceived length of the explanations in Figure 5. For the *visual modality*, 40 % of participants mention that highlighting some key items would have made it even easier and faster. In fact, introducing highlights would improve the visual interface, and would likely increase the differences in modalities that we already observe.

Finally, for all explanation conditions, 20-45 % of **participants would like to see more than one source containing an answer**. This means that the system would need to find multiple sources that converge to the provided answer. To provide users with this additional information without overloading cognitive capacity, an interactive strategy can be adopted. For example, evidence and additional sources can be presented through an explanatory dialogue (Miller, 2019), where users are initially provided with limited information, and more can be provided upon request.

5.3 What misleads users?

To better understand how explanations mislead users and how they can be further improved, we analyzed cases leading to user error. We compiled a set of unique questions alongside their frequency of errors across users in all explanation conditions.

A single annotator followed a similar coding procedure as previously described, where questions were analyzed in order to detect emergent error categories. Following this initial analysis, questions were categorized into error types. We found that users tend to be misled on the same questions, with most of the errors happening on around 50 questions per condition, and about 40 of these questions overlapping across conditions.

Below we describe the three main cases that we find:

Plausible explanations. A concept is plausible if it is conceptually consistent to what is expected or appropriate in some context (Connell and Keane, 2006). Work has consistently identified that peo-

ple often fail to evaluate the accuracy of information (Fazio and Marsh, 2008; Marsh and Umanath, 2013; Fan et al., 2020), particularly when no prior knowledge exists and information seems plausible (Hinze et al., 2014). We find many cases where a model response and explanation do not answer the question, yet the plausibility misleads users into accepting incorrect responses. For example:

Question: *Who is the patron saint of adoptive parents?*

Response: I am 37 percent confident that the answer is, **Saint Anthony of Padua**. I found the following evidence in a wikipedia passage titled, Anthony of Padua: Saint Anthony of Padua, born Fernando Martins de Bulhoes, also known as Anthony of Lisbon, was a portuguese catholic priest and friar of the Franciscan order.

Such errors make up 60 to 65% of the errors for all explanation conditions.

Lexical overlap. McCoy et al. (2019) describe 3 main heuristics exploited by NLI models: among them, lexical overlap. In our error analysis, the second most common mistake (from 30 to 35% of errors) that both *the model* and *the users* make is related to the lexical overlap between the question and the evidence. For example:

Question: *How many teams are in the MLB national League?*

Response: I am 60 percent confident that the answer is, **30**. I found the following evidence in a wikipedia passage titled, Major League Baseball: *A total of 30 teams play in the National League(NL) and American League (AL) , with 15 teams in each league .*

The evidence contains the correct answer (15 teams) but many users are misled by the phrase “*A total of 30 teams play in the National League*”.

Belief bias. Humans tend to rely on prior belief when performing reasoning tasks (Klauer et al., 2000). In model evaluation, this has consequences affecting validity. For example, if instructions are not specific, participants are left to use their beliefs to infer what is required of them, leading to varied interpretations. People often rely more heavily on belief bias when processing information under pressure (Evans and Curtis-Holmes, 2005), therefore in time limited evaluations this phenomenon might be more prominent. We reduced these confounds by carefully designing instructions, a straightforward interface, allowing workers plenty of time and removing ambiguous questions. However, some interesting cases of belief bias do occur — take for instance, the example below:

Question: *Where is the longest bone in the body found?*

Response: I am 17 percent confident that the answer is, **femur**. I found the following evidence in a wikipedia passage titled, Femur: The Femur or thigh bone, is the proximal bone of the hindlimb in tetrapod vertebrates .

Such errors in our evaluation make about 3-5% of total errors in each explanation condition.

6 Discussion

6.1 Why Explanations Worked for ODQA?

Our studies observed significant improvements from explanations for the end-task to help users decide whether to trust the prediction of an imperfect open-domain QA agent. A natural question then is why explanations worked for this task despite many negative results on other tasks, such as sentiment, LSAT, and computer vision (Bansal et al., 2020; Chu et al., 2020; Hase and Bansal, 2020). One hypothesis is that, in our task explanations provide user’s with new knowledge, previously unknown to them. For example, on a sentiment classification task, explanations highlight information in the text already visible to the users. In contrast, in ODQA, explanations in terms of evidence text provide users with the additional context that helps validate the system’s answers. This new evidence may be especially helpful to users who don’t know the answers to the question, which would often be the case for open-domain question answering.

However, its worth noting that like previous works, not all of our explanation methods provided significant value over confidence; *e.g.*, in Figure 3 we did not observe any significant differences between longer extractive explanations and confidence for the spoken modality. Thus the success from showing explanations still cannot be taken for granted but instead be measured using well-designed user studies.

6.2 Implications and Recommendations

Another interesting question is how can our findings inform future research in explainable NLP.

Develop modality-specific explanations Our results showed that the best explanation varied across the modalities, indicating that evaluating explanations on one modality (*e.g.*, using studies with visual UI) and deploying them on another (*e.g.*, voice assistant) can lead to sub-optimal deployment decisions. As a result, explanations should be eval-

uated in the task and settings in which they will be deployed in-the-wild.

Further study abstractive explanations

Longer explanations helped in the visual case, showing that communicating more evidence has potential to help users. But, they hurt in the spoken case, perhaps because longer explanations increase cognitive load on users. This may indicate a trade-off between *information content* of explanation and its *cognitive load* for ODQA. We had hoped abstractive explanations would achieve a more optimal balance between fidelity and comprehensibility for spoken. However, Figure 3 shows that they did not improve end-performance. One reason is that even though abstractive explanations were concise, they had high information density and thus did not sufficiently decrease cognitive load.

That said, while abstractive explanations did not significantly improve accuracy compared to longer explanations, they did improve user speed at the task by 2.2 sec (Table 3) and were satisfactory rated in terms of their perceived length compared to longer explanations (Figure 5). The utility of such generated explanations, over longer explanations, may further increase when explain multiple sources (*e.g.*, in Hotpot QA (Yang et al., 2018)) or candidate answers, where communicating multiple entire passages seems infeasible.

Enable interactive explanations All explanation conditions we tested were static—they assumed a single trade-off between detail and conciseness. For example, EXTRACTIVE-SENT always conveyed a single sentence to the user as an explanation, which was concise but may not always convey all context required to validate answers. A different strategy may be to use interactive explanations, in which the system first gives a concise explanation and then lets users request additional information. Such explanations may be especially used to accommodate user suggestions such as, including and explaining multiple candidate answers or multiple answers sources. Another possible strategy is to use *adaptive explanations*, where the model switches explanation strategies based on its confidence (Bansal et al., 2020).

Limitations While our user study addresses issues of many similar previous evaluations of explanations, it still has limitations. First, although the interaction of users with the QA system was

kept as realistic as possible, in reality users may have the option to double-check the model’s answer using external tools, such as Web search. Accommodating that case, would require encoding the additional cost of the reject action (*e.g.*, due to time spent and effort) into the payoff. In addition, unlike an interaction in-the-wild, questions were not posed by participants themselves, which may lead to different kinds of biases in the interpretation of the questions, as discussed before. Second, we conducted studies with MTurk workers who may not have the same motivation for performing the task as real users. To address this we incentivized them by rewarding high-performance through bonuses and penalties specified using a payoff matrix. In practice, the values of the payoff matrix can vary depending on the stake of the domain and may vary with users. Finally, we only registered hypothesis that compared performance on one metric—accuracy of error-detectability. However, there may be other metrics that may be of interest, *e.g.*, improvements in speed and user satisfaction.

7 Conclusion

Contrary to recent user-studies for other tasks (such as classification), ours suggest that for ODQA, explanations of model’s predictions significantly help end-users decide when to trust the model’s answers, over strong baselines such as displaying calibrated confidence. We observed this for two scenarios where users interact with ODQA model using spoken or visual modalities. However, the best explanation may change with the modality, *e.g.*, due to differences in users’ cognitive abilities across modalities. For example, for the spoken modality, concise explanations that highlight the sentence containing the answer worked well. In contrast, for the visual modality, performance improved upon showing longer explanations. Thus, developers and researchers of explainable ODQA systems should evaluate explanations on the task and modalities where these models will be eventually deployed, and tune these explanations while accounting for user needs and limitations.

Despite success of explanations on our domain, explanations sometimes still mislead users into trusting an incorrect prediction, and sometimes as often as displaying the baselines. These results indicate the need to develop better explanations or other mechanisms to further appropriate user reliance on ODQA agents, *e.g.*, by enabling abstractive expla-

nations that balance conciseness and detail while taking into account user’s cognitive limitations, interactive explanations that can explain multiple answer sources and candidates and adaptive explanations where model strategy changes based on its confidence.

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A Explanation Examples

In Table 2, we show an example of how the responses and explanations looked for each of the conditions. We also indicate in which modalities each explanation is shown in our experiments.

B Temperature Scaling

Temperature scaling (Guo et al., 2017), a multi-class extension of Platt Scaling (Platt et al., 1999), is a post-processing method applied on the logits of a neural network, before the softmax layer. It consists of learning a scalar parameter t , which decreases or increases confidence. t is used to rescale the logit vector z , which is input to softmax σ , so that the predicted probabilities are obtained by $\sigma(z/t)$, instead of $\sigma(z)$.

In our experiments, the model is set to pick from the top 100 solutions, however, in many cases the correct answer occurs within the top 10 items. For our purposes we calibrate the confidence scores of the top 10 outputs. We use the publicly available scripts provided by Guo et al. (2017).⁴

The model confidence before and after calibration can be seen in Figure 6.

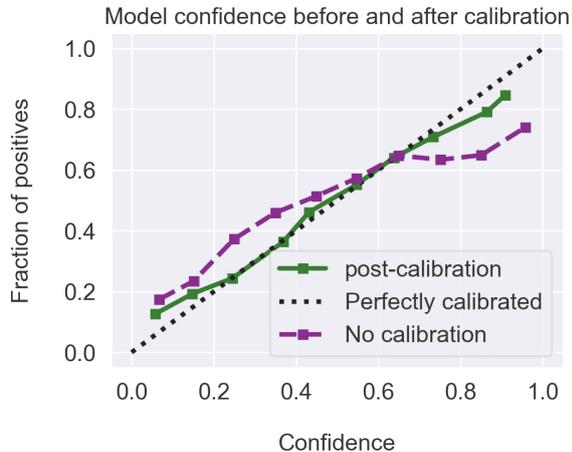


Figure 6: Confidence before and after calibration.

C Additional Preprocessing

Additional preprocessing to ascertain the quality of stimuli in each modality was required; more details can be found in Appendix . Before sampling questions for the task, to ensure a high-quality and non-ambiguous experience for MTurk workers, we manually filter out several “problematic” questions:

⁴https://github.com/gpleiss/temperature_scaling

- **Ambiguity in the question:** For various questions in NQ, multiple answers can exist. For example, the question: *when was King Kong released?*, does not specify which of the many King Kong movies or video games it refers to. These cases have been known to appear often in NQ (Min et al., 2020). We remove such questions from our subset.
- **The gold answer was incorrect:** Many examples in NQ are incorrectly annotated. As it is too expensive to re annotate these cases, we remove them.
- **Answer marked incorrect is actually correct :** We present both correct and incorrect questions to users. There are cases where the predicted answer is marked incorrect (not exact match) but is actually correct (a paraphrase). We manually verify that correct answers are paired with contexts which support the answer.
- **Correct answer but incorrect evidence:** The model sometimes, though not as often, chooses the correct answer but in the incorrect context. We discarded examples where the explanation was irrelevant to the question e.g. *who plays Oscar in the office? Oscar Nuñez, is a Cuban-American actor and comedian..* In order to be able to make more general conclusions about whether explanations help in error-detectability, we restrict our questions to ones containing correct answers in the correct context.
- **Question and prediction do not match type.** We removed cases where the question asked for a certain type e.g. a date, and the prediction type did not match e.g. a location.

In the visual modality, to ensure readability, we fixed capitalizations. For the spoken modality, to ensure fluency and clarity, we manually (1) inserted punctuation to ensure more natural sounding pauses, and (2) changed abbreviations and symbols to a written out form e.g. *\$ 3.5 billion* to *3.5 billion dollars*.

D Task Setup: Additional details

Platform and participant details We conduct our experiments using Amazon Mechanical Turk⁵.

⁵<https://www.mturk.com/>

EXPLANATION TYPE	RESPONSE+EXPLANATION	MODALITY
Baseline	The answer is, two .	Spoken
Confidence	I am 41 percent confident that the answer is, two .	Spoken
Abstractive	I am 41 percent confident that the answer is, two . I summarized evidence from a wikipedia passage titled, Marco Polo (TV series). Netflix cancelled the show after two seasons, as it had resulted in a 200 million dollar loss.	Spoken
Extractive-sent	I am 41 percent confident that the answer is, two . I found the following evidence in a wikipedia passage titled, Marco Polo (TV series). On December 12, 2016, Netflix announced they had canceled "Marco Polo" after two seasons.	Spoken/visual.
Extractive-long	I am 41 percent confident that the answer is, two . I found the following evidence in a wikipedia passage titled, Marco Polo (TV series). On December 12, 2016, Netflix announced they had canceled "Marco Polo " after two seasons. Sources told "The Hollywood Reporter" that the series' two seasons resulted in a 200 million dollar loss for Netflix , and the decision to cancel the series was jointly taken by Netflix and the Weinstein Company. Luthi portrays Ling Ling in season 1, Chew in season 2. The series was originally developed at starz, which had picked up the series in January 2012.	Spoken/visual

Table 2: **Explanation examples:** Example of how system responses looked for each explanation type and baseline, for the question *How many seasons of Marco Polo are there?*

We recruited 525 participants in total, with approval ratings greater than 95 % and had a maximum of 8 days for approval of responses in order to minimize the amount of spamming.

We use a random sample of 120 questions from our dataset which remains the same across all conditions. In order to keep each session per participant at a reasonable time and ensure the quality of the data wouldn't be affected by workers becoming exhausted, we opted for three fixed batches of 40 questions, all split as 50 % correct and 50 % incorrect. Workers could only participate once (only one batch in one condition). Participants took around from 35-45 minutes to complete the HITs, but were given up to 70 minutes to complete.

We monitored if their screen went out of focus, to ensure that participants did not cheat. We ensured that we had 25 user annotations per question. When analyzing the data, we remove the first 4 questions of each batch, as it may take participants a few tries before getting used to the interface. In the end, we collect about 21,000 test instances.

Task Instructions Imagine asking Norby a question and Norby responds with an answer. Norby's answer can be correct or wrong. If you believe Norby's answer is correct, you can accept the answer. If you believe it is wrong, you can reject it. If the answer is actually correct and you accept it, you will earn a bonus of \$0.15. But, if the answer is wrong, and you accept it, you will lose \$0.15 from your bonus. If you reject the answer, your bonus is not affected. (Don't worry, the bonus is extra! Even if it shows negative during the experiment, in the end the minimum bonus is 0). In total you will see 40 questions in this HIT (you will only be allowed to participate once) and the task will take about 40 to 45 minutes. You can be compensated a maximum of \$13.50 for about 40-45 minutes of work. Some things to note:

1. You must listen to the audio before the options become available.
2. If you make it to the end there is a submit button there, however, in case of an emergency you can hit the quit early button above and you will get rewarded for the answers you

provided.

- You can play the audio as many times as you need but as soon as you click a choice you will be directed to the next item.
- IMPORTANT!!** Please do not look up questions in any search engine. We will monitor when the screen goes out of focus, so please keep the screen on focus or you might risk being rejected.
- Finally, please do not discuss answers in forums; that will invalidate our results.

E Post-task survey

- I found the CLARITY of Norby’s voice to be:
(a) Excellent (b) Good (c) Fair (d) Poor (e) Very Poor
- I found Norby’s responses to be HELPFUL when deciding to Accept or Reject:
(a) Strongly Agree (b) Agree (c) Undecided (d) Disagree (e) Strongly Disagree
Can you give a few more details about your answer?
- I found the LENGTH of Norby’s responses to be:
(a) Too Long (b) Long (c) Just right (d) Short (e) Too short
- No AI is perfect and Norby is no exception. We are interested in helping Norby provide responses that can help users to determine whether to trust it or not (to accept or reject, just as you have done in this experiment). From your interaction with Norby, **do you have any additional feedback on what it can improve?**

F Results

F.1 Reward

We compute the differences in overall reward for each condition. We observe the same trends as we discussed for accuracy. More specifically, all explanation conditions improve the final user reward, with EXTRACTIVE-SENT performing best in the spoken modality and EXTRACTIVE-LONG performing best overall. These differences are shown in Figure 7.

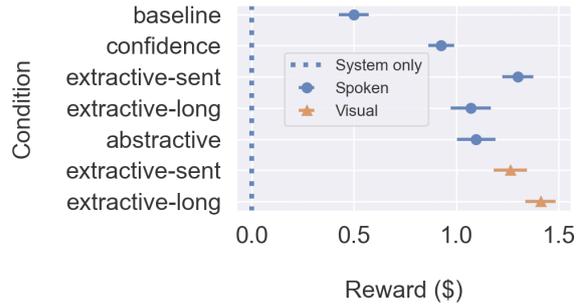


Figure 7: **Reward:** The scores presented here are out of \$ 2.70. Although all explanations are better than CONFIDENCE, the explanations leading to the highest rewards change across modalities.

F.2 Time Differences

We measured the time (in seconds) that it took participants to complete each question. In Table 3 we present the median times averaged over all workers per condition. We also include an adjusted time, subtracting the length of the audio, in order to measure decision time.

CONDITION	SEC/QUESTION	ADJUSTED
SPOKEN MODALITY		
Baseline	10.2 ± 1.6	8.3 ± 1.6
Confidence	9.4 ± 1.5	6.0 ± 1.5
Abstractive	24.4 ± 1.5	7.0 ± 1.4
Extractive-long	44.9 ± 1.6	9.2 ± 1.6
Extractive-sent	24.3 ± 1.7	7.6 ± 1.7
VISUAL MODALITY		
Extractive-long	16.1 ± 1.7	-
Extractive-sent	10.4 ± 1.1	-

Table 3: Time differences across modalities. Time differences in the right column have been adjusted by removing the duration of the audio files. We observe that with additional information, users can make faster decisions than the BASELINE condition.

F.3 Voice Quality

Participants in the spoken conditions rated how clear they found the voice to be. Around 90 % rated the voice as good or excellent. These results are shown in Figure 8.

F.4 Helpfulness

Differences in perceived helpfulness are shown in Figure 9.

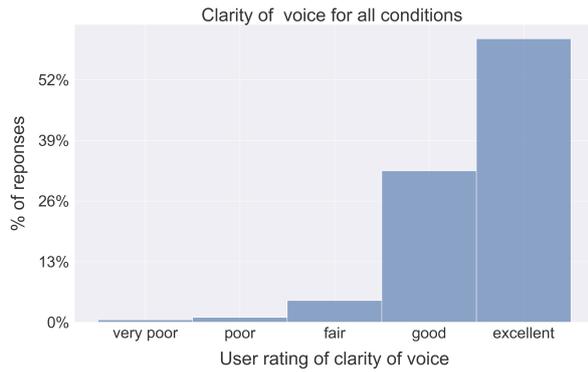


Figure 8: **Voice clarity:** Most participants found the voice of the assistant to be good or excellent.

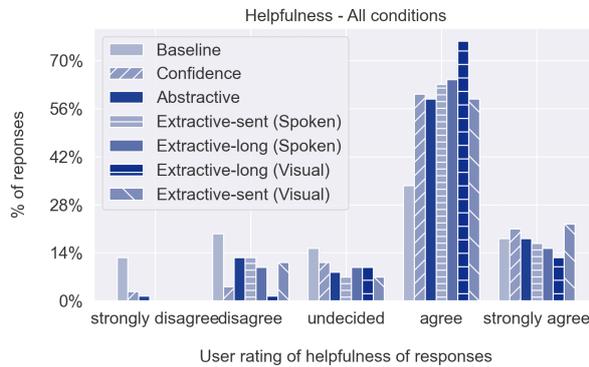


Figure 9: **Helpfulness:** Participants indicated how helpful responses were. These results reflect the large differences we see in performance (BASELINE vs the rest of the settings), but are not able to capture the more subtle differences among explanation strategies and CONFIDENCE.

F.5 User Feedback

Users provided free-form written feedback on possible ways to improve the system. The prompt they saw was: *do you have any additional feedback on what the system can improve?* After converging on a final set of codes, two annotators coded up about 400 responses across all conditions. The codes and their descriptions can be found in Table 4. The codes are *not* mutually exclusive.

We found that many users across most conditions, would like **adaptability features** added. Additionally, we found that participants would like to be provided with multiple sources which converge on the answer. We also observe that for spoken conditions, **improvements on length** are mentioned more often. The full distribution of codes across conditions is shown in Table 5.

CODE	DESCRIPTION	CATEGORY
len-conciseness len-expand	users wish explanation was shorter users wish explanation was shorter	improvement on length
adapt-detail adapt-voice	users wish details adapted with confidence users wish voice adapted to confidence	adaptability feature
pres-change-confidence pres-highlighting	users wish confidence would be communicated differently e.g. the answer is probably.... users wish important facts would be highlighted	improve presentation
need-more-sources need-confidence need-source need-explanation need-link need-multiple-answers	users wish more source were provided users wish confidence was provided users wished a source was provided users wish an explanation would be provided users wish a link was provided users wish more than 1 answer was provided	need additional info

Table 4: The codes used to uncover areas of improvement from the post-experimental user feedback.

CONDITION	CODE	% PARTICIPANTS
baseline	adapt-voice	50
	need-confidence	36
	need-explanation	25
	need-source	17
confidence	need-explanation	38
	adapt-voice	29
	pres-change-confidence	14
	adapt-detail	10
	need-multiple-answers	10
	need-link	5
extractive-sent (spoken)	need-more-sources	44
	adapt-detail	28
	len-conciseness	22
	need-multiple-answers	17
	need-link	11
	len-expand	11
	pres-change-confidence	6
extractive-long (spoken)	len-conciseness	78
	need-more-sources	15
	pres-change-confidence	4
abstractive	len-conciseness	52
	need-more-sources	22
	adapt-detail	22
	pres-change-confidence	13
	need-multiple-answers	4
extractive-sent (visual)	need-more-sources	33
	adapt-detail	33
	len-expand	27
	need-multiple-answers	7
extractive-long (visual)	pres-highlighting	40
	need-more-sources	33
	adapt-detail	10
	need-link	10
	pres-change-confidence	7

Table 5: Distribution of codes across all conditions. Codes are **not** mutually exclusive.