Uncalibrated Models Can Improve Human-AI Collaboration

Kailas Vodrahalli
Stanford University
kailasv@stanford.edu

Tobias Gerstenberg
Stanford University
gerstenberg@stanford.edu

James Zou
Stanford University
jamesz@stanford.edu

Abstract

In many practical applications of AI, an AI model is used as a decision aid for human users. The AI provides advice that a human (sometimes) incorporates into their decision-making process. The AI advice is often presented with some measure of "confidence" that the human can use to calibrate how much they depend on or trust the advice. In this paper, we present an initial exploration that suggests showing AI models as more confident than they actually are, even when the original AI is well-calibrated, can improve human-AI performance (measured as the accuracy and confidence of the human's final prediction after seeing the AI advice). We first train a model to predict human incorporation of AI advice using data from thousands of human-AI interactions. This enables us to explicitly estimate how to transform the AI's prediction confidence, making the AI *un*calibrated, in order to improve the final human prediction. We empirically validate our results across four different tasks—dealing with images, text and tabular data—involving hundreds of human participants. We further support our findings with simulation analysis. Our findings suggest the importance of jointly optimizing the human-AI system as opposed to the standard paradigm of optimizing the AI model alone.

1 Introduction

In safety-critical settings like medicine, AI is often integrated as interactive feedback, allowing a human to decide when and to what extent the AI's "advice" is utilized [29]. For example, in medical diagnosis tasks, this places the AI in a similar category as lab tests or other exams a doctor may order to aid in diagnosis. This mitigates the often black box nature of AI algorithms that limit a user's trust and usage of AI [6, 24, 34, 18].

Typically, these algorithms are designed and optimized to minimize loss using standard training objectives independent of the human end user. In this paper, we question this premise and ask whether a joint optimization of the entire human-AI system is possible. In particular, we revisit the conventional wisdom that models with calibrated confidence enable more accurate transfer of prediction uncertainty between models and/or humans [8]. We propose calibrating a model for human use, with the intuition that humans are often unable to accurately integrate calibration information correctly and so may benefit from uncalibrated information. This approach is complementary to existing ideas on how to help humans utilize AI advice (e.g., through some form of explanation accompanying the advice or through feedback on model/human performance) [36, 14].

We draw on prior work modeling human predictions [30] and assume black box access to an AI algorithm which provides advice. From data collected on thousands of human interactions, we fit a model for how humans incorporate (or ignore) AI advice. Using this learned human behavior model, we optimize a monotonic transformation that modifies the AI's reported confidence to maximize human-AI system performance (measured as the human's final accuracy). We demonstrate first in simulations and subsequently with real-world data using crowd-sourced human study participants

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that our modified AI advice results in higher overall performance. These results suggest there is merit to jointly optimizing human-AI systems and that an optimal AI algorithm may not be optimal for human use.

Our contributions We propose and empirically validate a framework for optimizing an AI algorithm with respect to the human end user, resulting in *human-calibrated AI* that calibrates AI models for human use. We only require black box access to the AI. Our framework relies on a model for human behavior, which we create using a large collection of empirical data on human interaction with AI advice. To the best of our knowledge, these are some of the first results using an empirically validated model for human behavior to optimize AI performance in a collaborative human-AI system. We would like to emphasize, however, that this these methods are not currently suitable for practical use.

Ethical considerations One of the main conclusions of our study is that human users do not consider confidence in the "optimal" way (i.e., how we model confidence in statistics). In an attempt to correct for this, we present both empirical and simulation-based evidence that modifying the presented AI advice improves overall performance. One potential question about our approach is: does modifying the AI's confidence constitute misleading the user? We agree – in our experiments, the AI can mislead the user. However, our goal here is not to propose a method that should be used in practical applications, and rather to highlight the importance of modeling human interaction when designing AI for human use.

Related works The experimental setup we use comes from the advice utilization community. Here, studies often use the JAS framework for measuring and comparing the effect of different forms of advice [28]. In many of these studies, algorithmic advice is manipulated to elicit various responses from humans. We take this a step further in our paper by manipulating the advice to improve model calibration with respect to the user and improve performance. Previous work has studied the effect of peer vs. expert advice [15], automated vs. human advice [22, 5, 15, 21], task difficulty [7], and advice confidence [25, 26]. Some work has also sought to characterize the perceptions people have of an AI when making decisions with AI advice and how these perceptions affect trust and utilization of the AI [13]. Of particular relevance to our work is [25], which provides evidence that uncalibrated, confident advice is more utilized by humans in certain settings. We also leverage a proposed model for human behavior from [30].

The conventional approach to human-AI collaboration is to ensure model and human calibration [8, 3] and to make the AI's predictions explainable [31, 27]. These explanations can affect human understanding of AI confidence [12, 35, 36, 14]. It is also standard practice to optimize the AI in isolation (i.e., maximize the AI performance). However, recent work suggests that the objectives used to optimize the AI do not adequately consider the human-AI team. Alternative approaches include learning to defer, where a classifier determines when expert input is required [16, 19]; learning to complement, where the AI is optimized to perform well on only the tasks that humans struggle with [33]; and methods that optimize objectives with costs assigned to requesting AI advice and/or human expert input utilization [1]. Our work is most related to [1], which also emphasizes the importance of confident AI predictions for human decisions. Our approach is complementary to these prior works and contains several novel aspects. We model human behavior using empirical data, demonstrate that this human model allows us to optimize the AI advice, and demonstrate both in simulation and empirically that our modified advice improves overall system performance. Furthermore, we only require black-box access to the AI advice. In relation to [1], we further differentiate our work as the model for human interaction is different – we give advice after the user makes an initial assessment.

2 Experimental setup

Our goal is to augment the performance of a human-AI system by optimizing the AI for use by a human. To make this goal tractable, we assume (1) that we have a model for human interaction with AI advice, and (2) that we have black box access to the AI algorithm producing the advice.

Human-AI interaction

The human-AI interaction involves two stages. First, a human is shown a task and completes it. AI advice is then presented, and the human is allowed to modify their response. As we measure performance before and after receiving advice, this model is conducive to studying the effect of advice and so sees common usage in the literature [22, 30, 17].

Data collection and tasks

We collected data from crowd-sourced participants on a diverse set of tasks that all have the same basic design. We focused on binary prediction tasks where humans respond on a continuous scale. The use of the continuous scale allows for a more rich analysis of the user's prediction than just the simple binary prediction label would permit.

Participants were shown a sliding scale with each end indicating a different binary response. They were instructed to move a pointer on the scale to the location that indicated their confidence and their response, with the midpoint on the scale indicating an uncertain response. Participants submitted an initial response; subsequently, the advice was indicated with a visual marker on the scale and participants were allowed to adjust their initial response. Participants were incentivized so that higher confidence in correct and incorrect answers increased and decreased their monetary reward respectively.

We collected data on a set of four tasks from diverse data modalities. These tasks were originally proposed in prior work [30]. The tasks were designed to be accessible to the general public to allow use of crowd-sourced study participants for obtaining empirical data. See below for a brief description of the tasks we used; examples of task instances from each of the four tasks are shown in Appendix B.2. The data collected is summarized in Table 1. Each task consists of 32 binary questions. For each task, the 32 questions were carefully selected to have a range of difficulty. More details on the distribution of task difficulty is presented in Appendix B.3.

All participants received the same set of questions, though the order was randomized for each participant. All participants also received the same advice, although a small amount of noise was randomly added for each participant. The advice had an accuracy of $\sim 80\%$ for each task; participants were informed of this accuracy. However, no feedback on AI or human accuracy on individual questions was provided during the experiment.

Since the datasets we are using are relatively small and curated primarily for human use rather than AI training, we opted to use aggregated human responses as a proxy for an AI model. In particular, the advice was constructed by averaging the responses of a prior group of human participants who responded to the questions without receiving any advice. This allowed us to ensure the advice given was "reasonable" in the sense that the advice is generally less confident on difficult tasks and more confident on easy tasks. We checked the calibration of this advice by computing the expected calibration error (ECE) [20]. The ECE for AI advice is 0.074, indicating the advice is roughly calibrated (0 indicates perfect calibration).

We recruited 49-79 participants for each task, resulting in several thousand datapoints (each question is one datapoint). Participants are US residents, roughly 50% are female, and the average age is approximately 30 years old. Despite limitations in the age distribution and geographic location of participants, a survey question we asked indicated a varied range of AI familiarity in our participants.

We followed standard practice in collecting data. Our study protocol was approved by our institution's IRB board. The data collection process was low risk, and we ensured samples contained diverse participants across age, sex, and ethnicity. We compensated participants at $\geq$ \$10.00 per hour (depending on bonus pay). The total cost was around \$600 (Section 2) + \$750 (Section 5.2).

We have four types of data with corresponding user tasks. **Art dataset (Image data)** Contains images of paintings from 4 art periods: Renaissance, Baroque, Romanticism, and Modern Art. Participants were asked to determine the art period a painting is from given a binary choice. **Cities dataset (Image data)** This dataset contains images from 4 major US cities: San Francisco, Los Angeles, Chicago, and New York City. The task is to identify which city an image is from given a binary choice. **Sarcasm dataset (Text data)** This dataset is a subset of the Reddit sarcasm dataset [10], which includes text snippets from the discussion forum website, Reddit. Participants were asked to detect whether sarcasm was present in a given text snippet. **Census dataset (Tabular data)** This dataset comes from US census data [32]. The task is to identify an individual's income level given some of their demographic information—e.g. state of residence, age, education level.

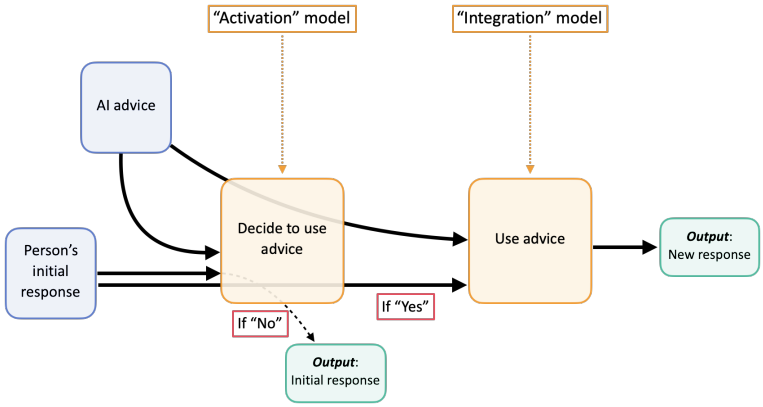


Figure 1: Activation-integration model for human behavior.

Table 1: Summary of data used for fitting our human behavior model. This data is publicly available at https://github.com/kailas-v/human-ai-interactions.

Task	# Participants	# Observations	Activation Rate	Accuracy (before advice)	Accuracy (after advice)
Art	68	2176	0.523	63.7%	75.5%
Cities	79	2528	0.557	70.7%	77.1%
Sarcasm	49	1567	0.347	72.7%	76.1%
Census	50	1600	0.475	70.1%	73.6%

3 Human behavior model

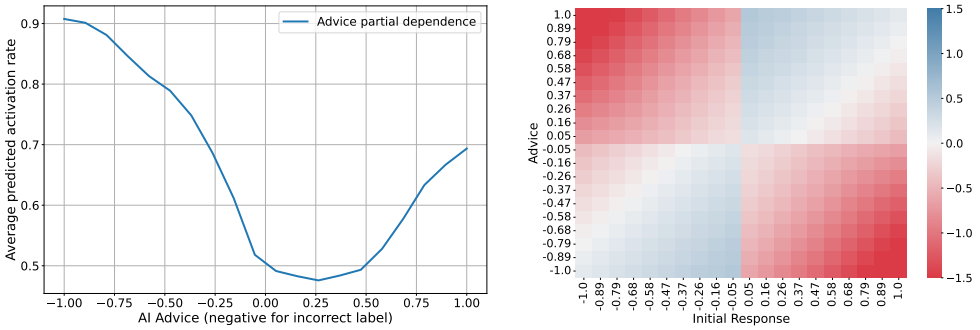
Table 1 provides a summary of the data collected for developing our human behavior model. We find that humans actually changed their response after receiving advice roughly 50% of the time, with the exact number shown in the "Activation Rate" column of Table 1. When a person does change their response, we call this person "activated." Specifically, a person is activated if their final response changes by at least a small amount.

This observation motivates a simple, two-stage model for human behavior: a human first decides whether to modify their response ("activation stage"), and subsequently, if they were activated, they modify their response ("integration stage"). A diagram of this model is shown in Figure 1. This two-stage model is consistent with previously proposed models from the psychology and HCI literature [9, 30].

We fit functions for each of the two stages: an activation model that predicts how likely it is that a person is activated, and an integration model that predicts how the person modifies their advice, assuming they are activated. Taken together, we can model human behavior in the two-stage human-AI system we use to run our experiments. We define this model's behavior more rigorously in Section 4. Our fitted models will only be used to optimize our advice-modifying function and will not be used a test-time. As such, we can utilize demographic information about the participants to fit the model, though such information may not be available during a real-world deployment. We opt to fit a small neural network for each of these stages, as we require a differentiable model (for easy optimization) with moderately more complexity than a linear model.

3.1 Activation model

Our activation model takes 12 input features extracted from a single person-task instance interaction. It outputs a probability for whether the person will be activated on the given task instance. The input features are based on the person's initial response, the AI advice, and several demographic features including age and sex. We do not encode the initial response or AI advice directly as the label (the



(a) Activation model – PDP for AI advice

(b) Integration model – Heatmap

Figure 2: Our trained model for human behavior: (a) Partial dependence plot measuring the effect of the advice on activation. (b) Heatmap of the average behaviour of our integration model for human behavior when we vary unmodified AI advice and the human's initial response.

left or right slider location of the correct answer) is randomized for each participant. Instead, we use the response and advice confidence, as well as a binary feature that encodes whether the response and advice agreed on the label. This implies a symmetry in the model's predictions. Please see Appendix D.1 for a description of all the features used.

We use a 3 layer neural network with ReLU non-linearities for the activation model. We also attempted to use other simple algorithms for modeling the activation behavior of humans, like linear models, but found the neural networks to perform better. We trained the network using binary cross-entropy loss with an Adam optimizer [11] and stopped training when validation loss increased, as is standard. The activation model achieves a ROC-AUC > 0.81 on held-out test participants, suggesting reasonable performance despite the high variability in our dataset.

In Figure 2a, we show a partial dependence plot for the learned activation model. This plot shows the average behavior (across our entire test dataset) of the activation model when we fix the AI advice to be a certain value (the x-value) for all data points. The AI advice can be positive (correct advice) or negative (incorrect advice), while the magnitude corresponds to the advice confidence. We note that (1) there is a base level of activation around 50% and (2) our activation model predicts people will be most activated when the advice is confidently incorrect. This occurs because (a) most people in our dataset get answers correct, on average, and seeing confident advice of the opposite label tends to make people change their initial response (e.g. by decreasing confidence even if the predicted label does not change). And because (b) confident advice that agrees with a person's initial response (whether correct or incorrect) tends to increase their confidence. We also observe that (3) the activation rate increase when advice is confident and correct for the same reason previously noted in (2b). The activation rate is lower for correct advice than for incorrect advice as most people in our dataset are, on average correct, which tends to invoke a smaller response.

3.2 Integration model

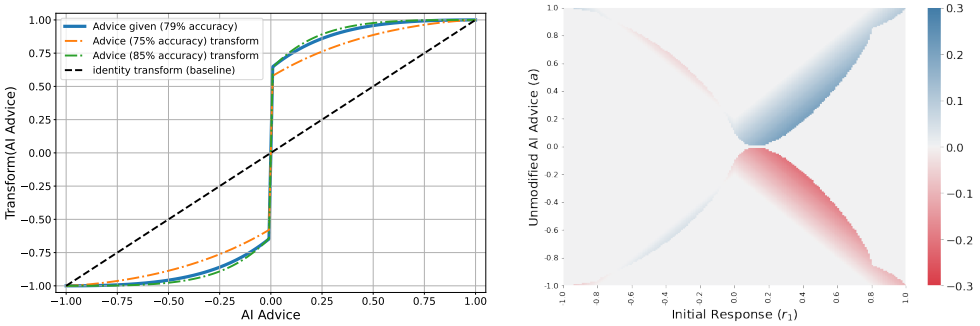
Our integration model is similar to our activation model, but optimized for a different function. In particular, we use the same input features, model architecture, and training procedure. The integration model outputs a prediction for $sign(r_1)(r_2 - r_1)$, where $r_1, r_2 \in [-1, 1]$ are the initial and final responses respectively. Note that r_1, r_2 are probabilities normalized to the $[-1, 1]$ scale. The training minimizes the RMSE between the predicted change and the actual change. The optimization is performed on only the subset of the dataset that was actually activated (roughly 50% of the data). Our integration model has a reasonable performance, with an RMSE of 0.25 (the maximum absolute error possible is 2) and R^2 of 0.73 on test data.

In Figure 2b, we plot a heatmap of the fitted integration model's behavior. We plot the average output of our integration model across our test data split when the person's initial response (x-axis) and AI advice (y-axis) are fixed to a certain value for all datapoints. The sign and magnitude of the initial response and AI advice correspond to correctness (negative is incorrect) and confidence. The

integration model prediction can be positive (increasing confidence in the initial predicted label) or negative (decreasing confidence in the initial predicted label / change in the predicted label).

We observe three features in the heatmap: (1) The heat map is symmetric across quadrants 1, 3 and 2, 4. This is by design. As the model does not use the initial response and AI advice values directly – it uses their magnitudes (confidence) as well as a third, binary term indicating whether they agree on label – the integration model can only predict a delta change relative to the sign of the initial response. (2) The output has largest magnitude when the advice is confident and opposite the person's initial response. (3) If the advice and the person's initial response share the same label, the integration model output is largest when the person's initial response has low confidence and the model has high confidence. These observations confirm our integration model has reasonable operation behavior.

4 Modifying the AI advice



(a) Fitted human behavior model (g_{α^*,β^*}) (b) Section 4.2 example

Figure 3: Simulation results. (a) Fitted modified advice vs. original unmodified advice. We show results across synthetically varied average advice accuracy in the training data. The curve labeled "Advice given" is what we actually show people in our experiments. (b) Optimal human-calibrated AI output for the setting described in Section 4.2. Heatmap shows delta change in advice compared to calibrated advice: red and blue values indicate where the AI should be under- and overconfident respectively in order to achieve the best human-AI system output.

Here we discuss how we modify the raw AI advice output. First let's establish some notation. The notation described below is in reference to a single datapoint; later, we will add the subscript i to index across datapoints.

Let $A \in \mathbb{R}$ denote the inverse sigmoid of the advice presented to participants (i.e., we present the AI advice as $\sigma(A)$). We will work with A rather than $\sigma(A)$ here, as we will aim to replace the σ transform with an optimized function that improves human-AI performance.

Let $g : \mathbb{R} \to [0, 1]$ be a function (which we will optimize) that maps the AI advice to a probability that the user is shown. Note that for the baseline, "unmodified advice," we set g to be the sigmoid function, $\sigma(x) = \frac{1}{1+e^{-x}}$.

Let r_1, r_2 be the initial and final responses from a participant (r_2 is a function of r_1, A, and other features), and let $y \in \{0, 1\}$ denote the true label. Let $\mathbf{u}$ represent demographic features of a person, and let $\mathbf{x} = (r_1, A, \mathbf{u})$ be the input feature vector to $f_{\text{activation}}$ and $f_{\text{integration}}$, our activation and integration models for human behavior models described in Section 3. To simplify notation, we let $f_{\text{integration}}$ denote the function that outputs the predicted r_2 for an activated person (rather than the delta from r_1 that we optimize for). Finally, let f_{HB} represent the entire model for human behavior. We assume all feature preprocessing is hidden inside $f_{\text{activation}}$ and $f_{\text{integration}}$ for convenience of notation.

4.1 Optimizing for human-AI performance

We consider g of the form

$$g(A) = g_{\alpha,\beta}(A) = \frac{1}{1 + e^{-\text{sign}(A)(\alpha|A|+\beta)}}, \tag{1}$$

where $\alpha, \beta \in \mathbb{R}_{\geq 0}$. Note that setting $(\alpha, \beta) = (1, 0)$ results in $g_{1,0} = \sigma$, the sigmoid function used to produce the unmodified advice. Note that we do not exactly perform a linear transformation on A: the $|A|$ and $\text{sign}(A)$ terms are included to ensure that g does not change the label recommended as it makes the function symmetric around $A = 0$. α modulates the rate at which the presented advice increases with AI confidence, while β adjusts the minimum confidence level of the presented advice. For example, if $\beta = 1$, the presented confidence is $> \frac{e}{1+e} > 0.73$ (relative to the chosen label). In general, we can use other differentiable functions for g; we chose the form in Equation 1 because it is easy to optimize, simple to understand, and is still flexible enough to fit our data.

As a shorthand for when we modify the features input to f_{activate} and $f_{\text{integrate}}$, we denote $g(\mathbf{x}) = (g(A), r_1, \mathbf{u})$. We will optimize for α, β to maximize the expected final accuracy using our human behavior model, f_{HB}. As discussed in Section 3, f_{HB} has the following representation:

$$f_{HB}(g(\mathbf{x})) = f_{HB}(g_{\alpha,\beta}(\mathbf{x})) = \begin{cases} r_1 & \text{w.p. } 1 - f_{\text{activate}}(g_{\alpha,\beta}(\mathbf{x})) \\ f_{\text{integrate}}(g_{\alpha,\beta}(\mathbf{x})) & \text{w.p. } f_{\text{activate}}(g_{\alpha,\beta}(\mathbf{x})) \end{cases}$$

We then solve the following optimization problem to obtain α, β:

$$(\alpha^*, \beta^*) = \arg\min_{\alpha,\beta} \mathbb{E}\left[L(f_{HB}(g(\mathbf{x})),\ y)\right], \tag{2}$$

where L is the binary cross entropy loss function. The expectation is taken with respect to the randomness in f_{HB} and the data distribution. Given training dataset D, we optimize the following expression:

$$\arg\min_{\alpha,\beta} \sum_{(\mathbf{x}_i, y_i) \in D} \mathbb{E}[L(f_{HB}(g(\mathbf{x}_i)),\ y_i)] =$$

$$\arg\min_{\alpha,\beta} \sum_{(\mathbf{x}_i, y_i) \in D} L(r_{1_i},\ y_i) \cdot (1 - f_{\text{activate}}(g(\mathbf{x}_i))) \ + L(f_{\text{integrate}}(g(\mathbf{x}_i)),\ y_i) \cdot f_{\text{activate}}(g(\mathbf{x}_i))$$

In practice, we carry out this optimization using stochastic gradient descent, which is possible as we choose f_{activate} and $f_{\text{integrate}}$ to be differentiable functions (see Appendix D.2). For data, we used the empirical data described in Section 2. The full training procedure is visualized in Figure 4.

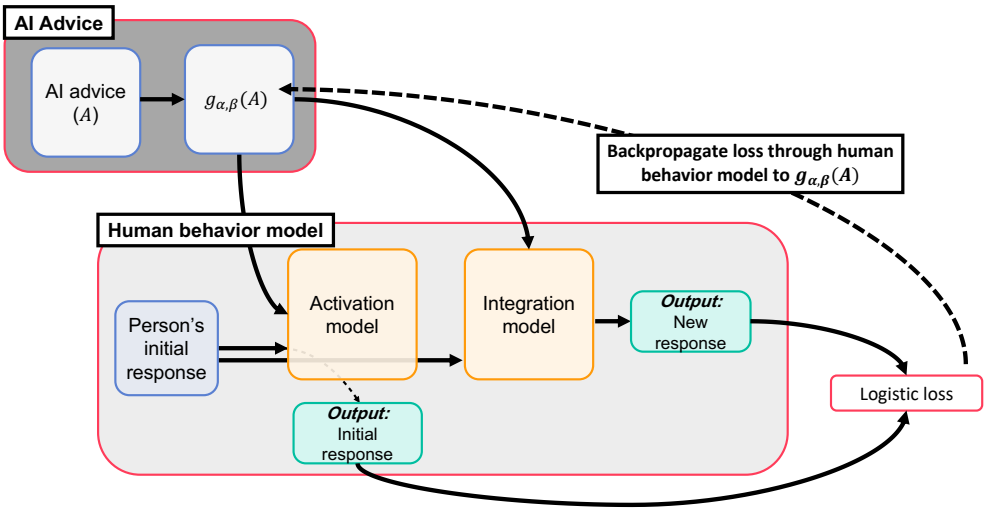


Figure 4: Overview of optimization procedure for $g_{\alpha,\beta}$. AI advice is input through $g_{\alpha,\beta}$. The transformed advice is then input into the human behavior model. Finally, loss is computed and the gradient with respect to the loss is backpropogated to update α and β. Note here that the human behavior model was trained previously and is now fixed.

Once we have optimized for α^*, β^*, we can apply it to new data without needing the user demographics $\mathbf{u}$ (i.e., we do not personalize the confidence transformation to individual users). Note that the choice of loss function is arbitrary here (we used logistic loss as our task is binary classification). In particular, for high risk settings where a mistake is very costly, the α^*, β^* could be selected accordingly using an appropriate loss function.

Table 2: Simulated performance difference of modified advice ("Advice given" curve in Figure 3a) to unmodified advice. Positive difference indicates higher value for modified advice. Results shown across three average advice accuracy levels. The bolded row is the advice used in our human experiments.

Advice Accuracy	Final Accuracy	Correct Confidence	Activation Rate
75%	+0.7%	+0.097	+0.083
79%	**+1.9%**	**+0.114**	**+0.091**
85%	+3.1%	+0.131	+0.111

4.2 When does under/overconfident advice help?

Here we describe simple theoretical situations where uncalibrated advice improves performance. We consider a binary classification task and assume we want to minimize the logistic loss of the human-AI classifier. We also assume (1) a constrained version of the activation-integration model perfectly models human behavior; in particular, humans either use their initial response or follow the given advice exactly. And (2) we have an oracle for human behavior and know exactly the calibration of the human and AI advice. We will now construct a function $f(a, r_1)$ that outputs a^*, the optimal advice to minimize logistic loss of the human-AI system.

To select a^*, we need to consider two quantities:

$$L_{r_1} = -\left[p_{r_1}\log(r_1) + (1-p_{r_1})\log(1-r_1)\right] \tag{3}$$

$$L_{a^*} = -\left[p_a\log(a^*) + (1-p_a)\log(1-a^*)\right] \tag{4}$$

Here, p_a and p_{r_1} are the probabilities the advice and initial response are correct respectively. Then L_{r_1} relates the log-loss for non-activated humans and L_{a^*} relates the log-loss of following the modified advice, a^*.

Now we simply select a^* to minimize the expected loss incurred by the human-AI system

$$a^* = \arg\min_{a'} \; (1 - p_{\text{activation}})L_{r_1} + p_{\text{activation}}L_{a'} \tag{5}$$

for $p_{\text{activation}} = f_{\text{activation}}(a^*, r_1, \mathbf{u})$ (which we assumed we know exactly). For example, consider a setting where

$$p_{\text{activation}} = \mathbb{1}[\bar{r_1} + \epsilon < \bar{a}]$$
$$p_{r_1} = f(r_1)$$

where $\bar{x} = \max\{x, 1-x\}$, $\epsilon \in [-0.5, 0.5]$, and for a generic function $f : [0,1] \to [0,1]$. Here a human under/overvalues their response relative to the advice (depending on ϵ), and the human is not calibrated (depending on f). In this setting, it is indeed optimal for the advice, a^*, to be under/overconfident to correct for human misutilization of advice (depending on the advice and initial response). An example where $\epsilon = 0.1$ and $f(r_1) = r_1^2$ is shown in Figure 3b. Further discussion is included in Appendix C.

5 Results

5.1 Simulation results

Optimizing Equation 2 results in an optimal α^*, β^*. Using f_{HB}, we can then analyze the expected benefit of g_{α^*,β^*} over the baseline, $g_{1,0}$. In Figure 3a, we show g_{α^*,β^*}. We plot three separate curves. The curve labeled "Advice given" is optimized using the previously described dataset, and this is the function we use in our empirical results. We also synthetically modify the dataset by biasing the advice towards the correct label and adding noise to the advice to respectively increase and decrease the average advice accuracy in the dataset to 75% and 85%. We then fit a new (α, β) to the modified dataset and plot these curves. Note that f_{HB} is fit to the unmodified dataset and is fixed for optimizing all three of these curves.

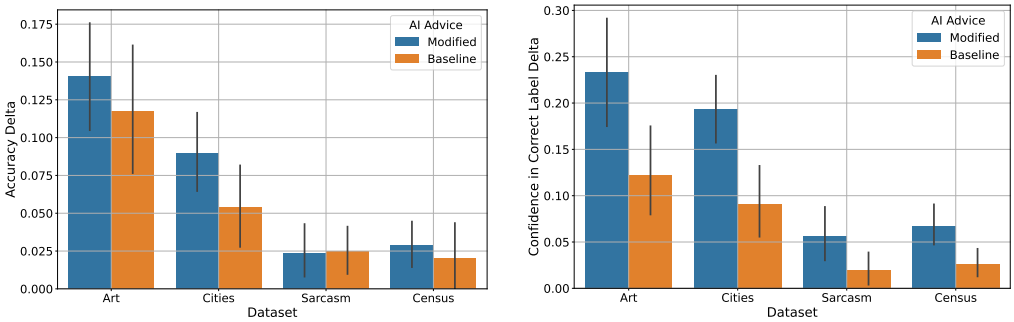
Table 3: Empirical performance on UK-based participants. Showing the difference in metric between modified advice and baseline (value is > 0 when modified advice resulted in a larger value). We recruited 50 participants for each task.

Task	Final Accuracy	Correct Confidence	Activation Rate
Art (90%)	+8.5%	+0.150	+0.101
Cities (87%)	+1.7%	+0.140	+0.169
All (89%)	**+5.2%**	**+0.149**	**+0.143**

For all three curves, we notice there is a large discontinuity at $A = 0.5$. This is a result of a large β^*, and suggests that advice is not useful to humans unless it is at a certain level of confidence (e.g., to make the human activated).

That all three curves follow relatively similar paths suggests the performance of g_{α^*,β^*} may be robust to small changes in advice accuracy. This is confirmed (in simulation) in Table 2, where we show the simulated performance difference between modified and unmodified advice. We see here that the final accuracy, confidence in correct result, and activation rate all increase with the modified advice.

5.2 Human experiments



(a) Accuracy (b) Confidence

Figure 5: Our empirical results: we plot the average change between the first (before advice) and second (after advice) responses in (a) accuracy and (b) confidence of the correct label, averaged by participant. These results are consistent with our simulation findings of Table 2. The error bar represents ± 1 standard deviation.

We verify our simulation results across the four previously described tasks (with the exception that we do not add noise to the advice, so all participants see the exact same advice now). Adult, US-based participants were recruited through the Prolific crowdworker platform [23]. We recruited 50 participants for each task, and randomly assigned either the unmodified (baseline) or modified advice to each person. In Figure 5, we show the average change in (a) accuracy and (b) confidence of the correct label (the average confidence, with correct and incorrect labels receiving positive and negative weight respectively), partitioning by the advice received by participants. Accuracy and confidence increase across all tasks when using advice ($p = 3.84 \times 10^{-6}$). Moreover, we can largely confirm our simulation results. Accuracy and confidence increased due to the modified advice across nearly all tasks. Additionally, activation rate (not plotted) increased with the modified advice, with an average increase of 3.3% across tasks.

Another interesting finding is that tasks with higher advice accuracy (Art and Cities) exhibit larger increases in accuracy and confidence. The AI advice is more accurate in Art and Cities (accuracy: 90% and 87%) compared to Sarcasm and Census (accuracy: 78% for both). This intuitively makes sense – we are making the advice more confident in its predictions, and so while this benefits all tasks, it disproportionately benefits tasks where the advice is more accurate. This effect was predicted by our simulation results.

Our primary human experiments involved US-based participants. To show our findings generalize, we took the advice modification learned on the US data and applied it to new participants based in the UK for the Art and Cities tasks. The findings are highly consistent: modified advice increases activation and improves final human accuracy and confidence (Table 3). Combining US and UK data, performance improvement is significant for both accuracy ($p = 8.86 \times 10^{-3}$) and confidence ($p = 4.43 \times 10^{-11}$).

6 Discussion, Limitations, and Future Work

In this paper, we proposed optimizing a simple function to better calibrate AI advice for human use in a collaborative human-AI system. To optimize the reported confidence, we trained a human behavior model from experimental data and used it simulate the full human-AI system. The modified AI advice are explicitly uncalibrated, but in both simulated and empirical results, it resulted in substantially higher final human performance. We further validated our model using new participants from a different country. These results highlight the importance of recognizing that AI, when deployed in collaborative systems, should not be optimized in isolation. Our results also suggest that we can view modifying AI advice as a *nudge* for the human user. If the AI says its confidence is 0.7, the user may not fully absorb the import of 0.7 since humans are not great at intuitive probability. Modifying the reported confidence could be a useful nudge to help users to better absorb the information. This view is supported by prior work suggesting humans prefer clean decision boundaries [2].

Our work has several limitations that would be interesting to address in future studies. In particular, it is unclear how reliable such a method would be in practice. We argue that our method for creating *human-calibrated AI* can be deployed in practice, but requires an accurate model for human behavior. In particular, if we have access to an oracle for an individual's utilization of AI advice, we can exactly optimize the output of a calibrated AI model to correct for the individual's biases. Note that this may lead to under- or overcalibrated advice depending on the user and the advice confidence. However, as we cannot perfectly model any given individual, the question to ask is whether we can create a robust model for human behavior (e.g., with confidence intervals etc.) and then optimize with respect to that model while accounting for error. This extension was out-of-scope for this paper, and is an important direction of future research. Other limitations include: we considered tasks where advice accuracy generally exceeded individual human performance and did not evaluate expert tasks (e.g., involving clinicians making clinical decisions). We also did not consider how human interaction with an AI evolves over time – that is, we assumed each individual to be static over the course of the study, while in general, humans may naturally adapt to the AI and modifying the AI may affect this process. These are also important directions for future research. Finally, we recognize that the human behavior model we used in this work does not capture all real-world settings. It may be important to consider different models for different applications, and our results will need to be validated in these new settings.

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Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes]
   (c) Did you discuss any potential negative societal impacts of your work? [Yes]
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [Yes]
   (b) Did you include complete proofs of all theoretical results? [Yes]
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] We include instructions and materials to reproduce experimental results in the Supplement.
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] In addition to details included in the paper, we include additional details in the Supplement.
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes]
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [N/A] Compute resources were minimal (i.e., could be run on a single core laptop in under a minute)
4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...
   (a) If your work uses existing assets, did you cite the creators? [Yes]
   (b) Did you mention the license of the assets? [No] The assets are all for public use and we cite the references.
   (c) Did you include any new assets either in the supplemental material or as a URL? [No]
   (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [N/A]
   (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes] Sarcasm dataset was filtered to omit potentially offensive content.
5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [Yes] In appendix
   (b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [Yes]
   (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [Yes]

A Appendix

Here we provide some additional information on our study design and dataset (Appendix B), when under/overconfident advice can help (Appendix C), our human behavior model (Appendix D), crowd-sourced data collection (Appendix E), the survey shown to empirical study participants (Appendix F), and additional results using step functions for the modified advice (Appendix G).

B Study Design and Data

B.1 Study design

In Figure 6, we visualize the study design described in Section 2. A human first completes a task on their own (Response 1). They then are given advice from an AI algorithm and are allowed to change their answer (Response 2).

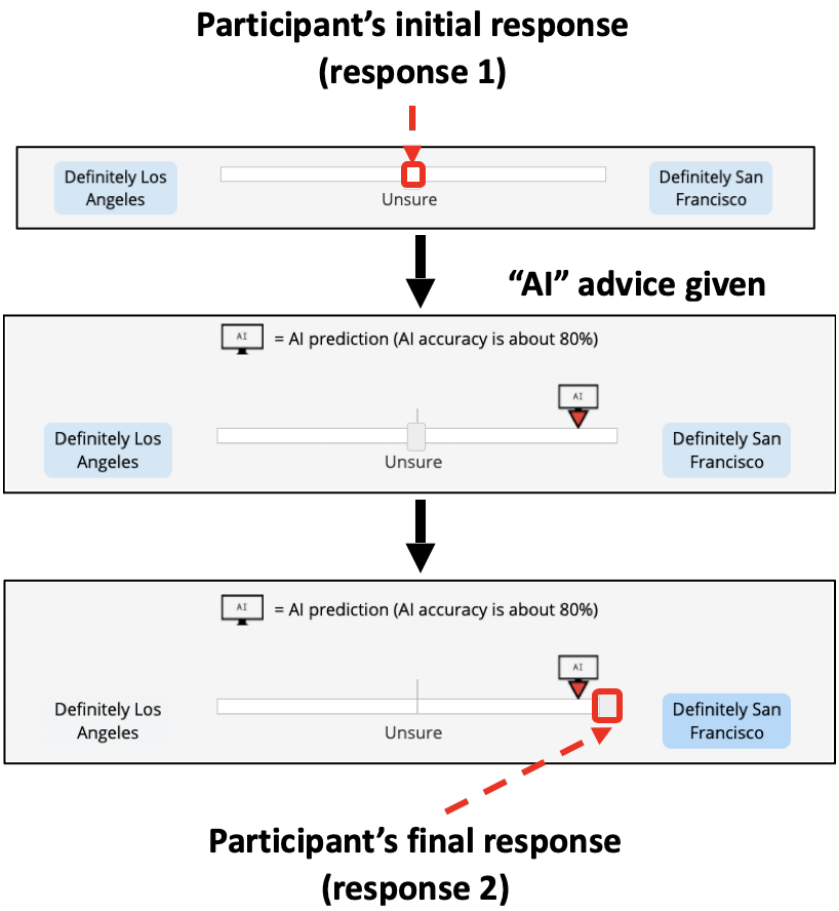
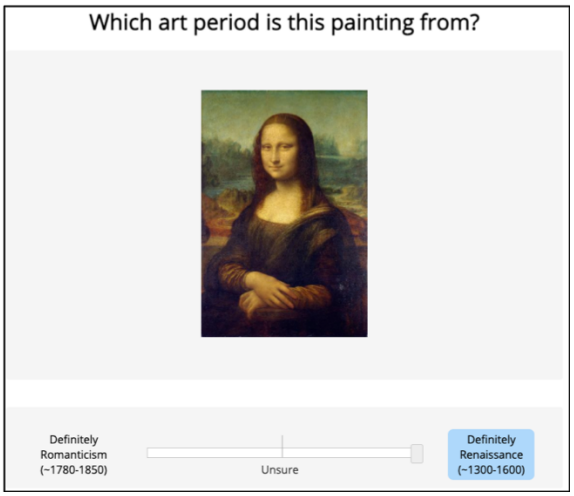


Figure 6: Visualization of our experimental setup.

B.2 Tasks

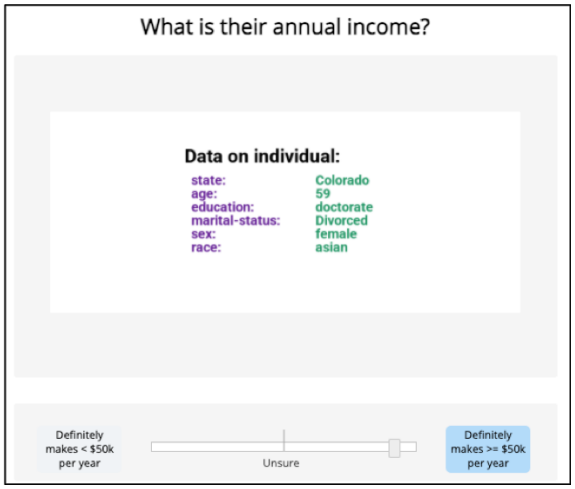
In Figure 7, we show example questions from each of the four tasks described in Section 2. For each task, questions were chosen to have a wide range of difficulties – in Figure 8, we show the probability density function of the advice across all four tasks. The mean advice across questions is indicated by the dotted vertical lines – it is similar across all four tasks.



(a) Art dataset

(b) Cities dataset

(c) Sarcasm dataset



(d) Census dataset

Figure 7: Example tasks for each of the four datasets we use.

B.3 Unmodified AI advice

In Figure 8, we plot the probability density function of the advice for each of the four tasks. Positive and negative values indicate correct and incorrect advice respectively. The magnitude of the advice indicates confidence. Notice that (1) the advice is skewed towards the right as the advice is roughly 80% accurate, (2) the average advice (indicated by the vertical dotted lines) is similar across all four tasks, and (3) the quality of advice given is fairly diverse, with each task having questions with incorrect and low-confidence advice.

In Figure 9, we visualize the calibration of advice confidence. As was mentioned in Section 2, the expected calibration error (ECE) is calculated to be 0.074 indicating the advice is well calibrated.

B.4 Summary of baseline performances

In Table 4, we summarize the baseline human and advice accuracies (i.e., before any interaction between the human and AI has occurred).

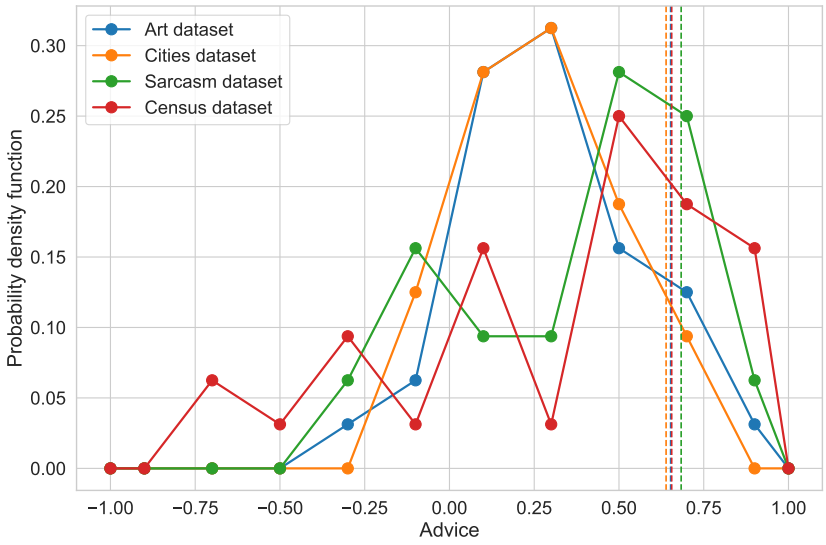


Figure 8: Distribution of advice confidence for all four tasks. Negative values indicate incorrect advice and positive values indicate correct advice. Dotted lines indicate mean advice across questions.

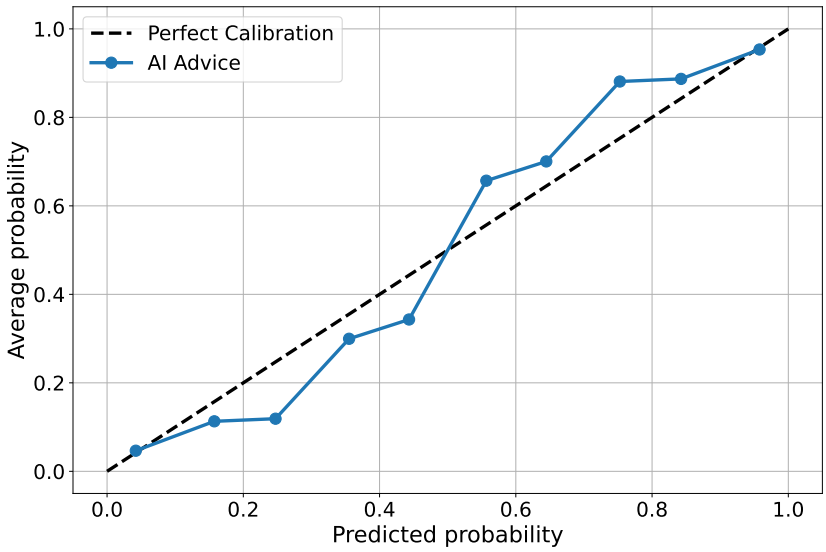


Figure 9: Calibration plot of the AI advice, aggregated across all four tasks. We note that the advice is roughly calibrated with an expected calibration error of 0.074.

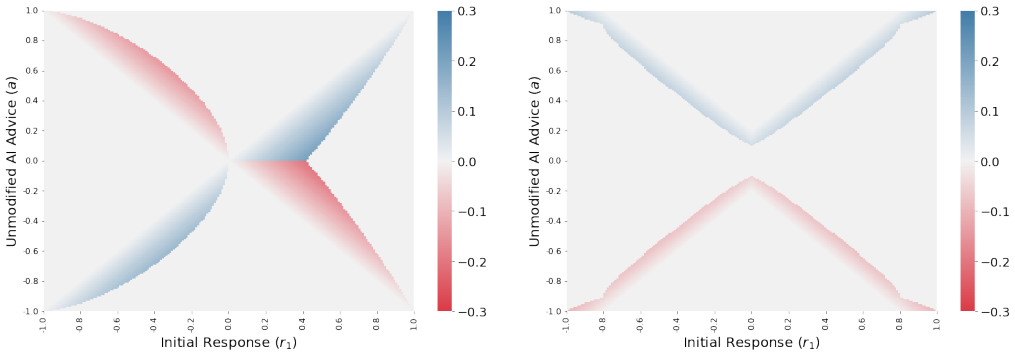
C Under- and Overconfident Advice

Here we provide additional examples for when under/overconfident advice is beneficial. We make the same assumptions from Section 4.2; they are repeated below:

1. Our goal is to minimize the logistic loss of the human response after receiving AI advice (we consider only binary classification problems here).
2. Humans either use their initial response or follow the given advice exactly. This is a constrained version of the activation-integration model.
3. We have an oracle for human behavior and know exactly the calibration of the human and the AI advice.

Table 4: Overview of baseline human and AI accuracies (before human-AI interaction occurs).

Task	Human Accuracy	AI Accuracy
Art	63.7%	90.1%
Cities	70.7%	87.5%
Sarcasm	72.7%	78.1%
Census	70.1%	78.1%



(a) Miscalibrated human (b) Biased human

Figure 10: Optimal human-calibrated AI output for two settings. Heatmap shows delta change in advice compared to calibrated advice: red and blue values indicate where the AI should be under- and overconfident respectively in order to achieve the best human-AI system output.

C.1 Miscalibrated human

Consider the case where $p_{r_1} = r_1^2$ – that is, the human is miscalibrated (in particular, underconfident for Label 0 but overconfident for Label 1 predictions). We show in Figure 10a the optimal modification to a calibrated AI advice to correct for the human's miscalibration. This modified advice is optimal in the sense that it minimizes the logistic loss of the human's final response given (potentially modified) advice, assuming the aforementioned model for human behavior.

The left region indicates the advice should as underconfident to compensate for the human's underconfidence in this region. This results in a decrease in confidence when the advice is predicting Label 1 and an increase in confidence when the advice is predicting Label 0. Recall that in the assumed setting, the human selects to follow the advice exactly whenever it is perceived to be more confident than the human is in their initial response. This results in symmetric behavior across the label boundary.

Similarly, the right region indicates the advice should be overconfident to compensate for the human's overconfidence in this region.

C.2 Biased human

Consider the case where the human is biased when valuing their response compared to the advice. In particular, $p_{\text{activation}} = \mathbb{1}[\bar{r_1} + \epsilon < \bar{a}]$ (here $\bar{x} = \max\{x, 1-x\}$), with $\epsilon = 0.1$. Here, the human is overvaluing their own response – they only use the advice when the advice confidence exceeds their own confidence by the margin, ϵ.

In Figure 10b, we show how to modify the advice to compensate for this bias. As the human is undervaluing the AI advice, the modified advice only increases the confidence of the AI in certain conditions (this corresponds to a positive delta when the predicted labels is "1" and a negative delta when the predicted label is "0").

Note there is a gap between $0.45 - 0.55$ for the unmodified advice where no modification is recommended. This gap results from being unable to decrease the logistic loss when the advice is

sufficiently unsure. For the advice to have an impact, it must be presented as more confident than the human by at least ϵ; however, for regions where the advice truly has low confidence, presenting the advice as overconfident results in higher logistic loss.

C.3 More complex examples

Now consider taking together the two modifications from the above settings – $p_{r_1} = r_1^2$ and $p_{\text{activation}} = \mathbb{1}[\bar{r_1} + 0.1 < \bar{a}]$ for $\bar{x} = \max\{x, 1 - x\}$. This gives us the scheme for modified advice shown in Figure 3b.

C.4 Uncalibrated AI Assumption

In our analysis, we assumed the AI was calibrated. This is necessary – if the advice is not calibrated, we cannot optimize the advice as we do not know the value of p_a.

However, if we are given uncalibrated advice but are able to calibrate that advice, it is possible to remove this assumption. In particular, the optimal modified advice will be a composition of a calibration function and the modification based on that calibrated advice.

C.5 Optimization procedure

We optimize each advice-initial response pair separately. For each advice-initial response pair, we compute the optimal modified advice using a line search method with a step-size of 5×10^{-3}.

In general, the candidate for the optimal value of modified advice is the advice with the smallest change in advice confidence that results in the human being activated. If following this modified advice results in a higher logistic loss, then the optimal modified advice will be to make no modification.

D Human Behavior Model

D.1 Features for the human behavior model

Here we detail the features used for our activation and integration models ($f_{\text{activation}}$ and $f_{\text{integration}}$). Features and a description are given in Table 5.

Table 5: Description of input features for $f_{\text{activation}}$ and $f_{\text{integration}}$ models.

Feature #	Value Range	Description
1	$[0, 1]$	Response 1 Confidence
2	$[0, 1]$	Advice Confidence
3	$\{-1, +1\}$	$+1$ if Advice and Response 1 agree on label, otherwise -1
4	$[-1, 1]$	Feature 1 $\cdot$ Feature 3
5	$[-1, 1]$	Feature 2 $\cdot$ Feature 3
6	$[-1, 1]$	Survey question measuring human's perception of AI performance on the given task
7	$\mathbb{R}_{\geq 18}$	Age
8	$\{0, 1\}$	Sex
9	$\{0, 1\}$	Does the person have prior experience with computer programming?
10	$[1, 10]$	Self-reported socioeconomic status
11	$[0, 1]$	Survey question assessing perceived presence of AI in person's life
12	$[1, 8]$	Self-reported education level

D.2 Human behavior model training procedure

The activation and integration models are three-layer fully-connected neural networks with ReLU activations. The layer sizes are (1) 12×24, (2) 24×12, (3) 12×1. We trained our models using

the empirical data described in Section 2. We optimized our models using the Adam optimizer with learning rate 1×10^{-3} and no weight decay. We used early stopping to avoid overfitting.

E More Details on Crowd-Sourced Data Collection

Here we include additional details on the crowd-sourced data collection procedure we run.

E.1 Demographic information collection

Our experiments were run on Prolific [23]. The demographic information used by our activation-integration model was provided by Prolific. Education level is defined on a scale from 1 to 8, and should be interpreted as:

1 – Don't know / not applicable

2 – No formal qualifications

3 – Secondary education (e.g. GED/GCSE)

4 – High school diploma/A-levels

5 – Technical/community college

6 – Undergraduate degree (BA/BSc/other)

7 – Graduate degree (MA/MSc/MPhil/other)

8 – Doctorate degree (PhD/other)

Socioeconomic status is defined on a scale from 1 to 10 and was assessed by asking participants to answer the question shown in Figure 11.

Socioeconomic Status

Participants were asked the following question: Think of a ladder (see image) as representing where people stand in society. At the top of the ladder are the people who are best off—those who have the most money, most education and the best jobs. At the bottom are the people who are worst off—who have the least money, least education and the worst jobs or no job. The higher up you are on this ladder, the closer you are to people at the very top and the lower you are, the closer you are to the bottom. Where would you put yourself on the ladder? Choose the number whose position best represents where you would be on this ladder.

Figure 11: Socioeconomic status question.

E.2 Survey questions

Participants were asked two survey questions. We used their responses in our activation and integration models. The questions were:

1. Do you think the AI or the average person (without help) can do better on this task?
2. How often do you use AI systems to aid you in your everyday life and/or at work?

Participants responded to each question on a slider scale. The first question was intended to measure participant's perceived confidence in the AI prior to doing any tasks. The second question was intended to measure the participant's familiarity and comfort with AI.

E.3 Participant compensation

We compensated participants at $\geq \$10.00$ per hour (depending on bonus pay) as per the recommended rates by Prolific. We informed participants of the possibility for bonus pay. Bonus was calculated as:

$$\text{bonus} = \begin{cases} 0 & \text{if } S < 0.3 \\ S * 0.3 & \text{otherwise} \end{cases}.$$

Here, S is the average performance, computed as (the average of)

$$sign(\text{correct response}) \cdot \text{response}_1,$$

where $-1 \leq \text{response}_1 \leq 1$.

F Participant Instructions

Our study was designed using standard methods [28]. We implemented our study as a simple web app using jsPsych [4] with a Python-based web server. This was necessary to (1) customize our survey design and (2) deploy our survey to crowd-sourced survey participants.

Here we describe the survey shown to participants. In the "example-survey-slides" folder of the supplementary material, we include a set of PDF documents showing screenshots of our survey for the Art dataset for a participant. Each "page" in the directory corresponds to a separate web page. Filenames are numbered in the order a participant encounters them. Clicking "continue" / "submit" brings the participant to the next web page.

A brief description of the survey. Any content referring to the art data was substituted with appropriate language for the given task.

1: Participant enters a unique ID assigned to them through Prolific [23], the crowdsource platform we use to recruit participants.

2: Instructions specific to the task and advice source participants will receive. Note that this page is seen by participants as a single, continuous web page.

3: Additional information on the advice source.

4: Information on bonus payment.

5: Manipulation check. Participants who got the wrong answer were sent back to Page 2.

6: Pre-survey question to assess prior belief in AI advice

7: Example task: recording Response 1.

8: Example task: recording Response 2.

9: After completing all tasks, Participants are shown this screen.

10-14: Additional survey questions.

15: Check for errors in survey.

16: Debrief slide.

17: Bonus payment and survey submission slide.

G Additional Results

G.1 Other AI modification functions

We additionally ran experiments to compare other modification functions to the sigmoid-like $g_{\alpha,\beta}$ function we used to modify the AI in the main experiments. In particular, we consider two variants of a step function:

$$g_{step,\lambda}(x) = \begin{cases} \lambda & \text{if } x \geq 0 \\ -\lambda & \text{if } x < 0 \end{cases}$$

for some $\lambda \in (0, 1]$. For our experiments, we chose $\lambda \in \{0.50, 0.95\}$. We visualize these transform functions in Figure 12.

The idea of using a step function is to remove all information about advice confidence. We present the information in the same way as other experiments to remove possibility that the presentation affects human decision making. The two lambdas we selected allow us to compare showing whether showing some variation of confidence in the binary output of the AI affects human usage.

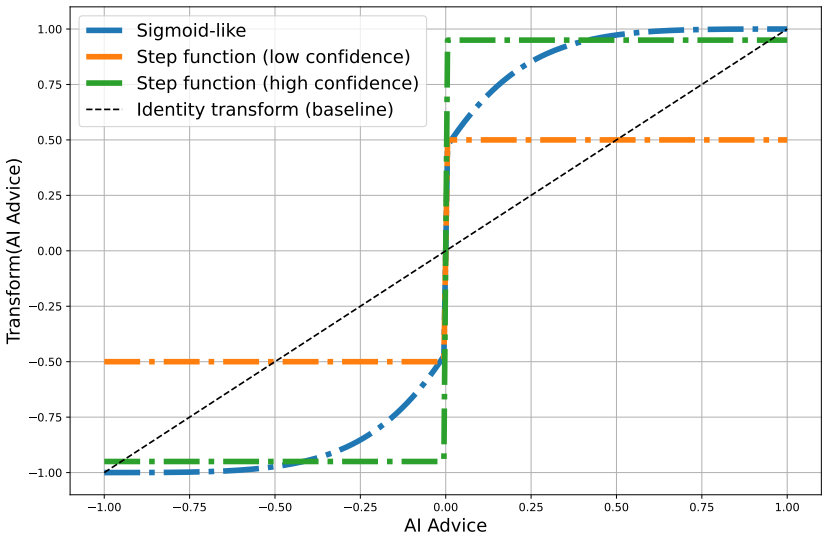


Figure 12: Visualization of the transform functions we evaluate in additional experiments.

We compare the performance of each of these functions by recruiting 100 adult US-based participants and randomly assigning each to a different modified advice. The experiment was conducted using the painting identification task. All other aspects of the recruitment process and study design are the same as used in the main study.

Results are summarized in Table 6. As there are variations between the people in each group (and their performance on the tasks before seeing advice), we use binned averages of the metrics. In particular, we place each human-AI interaction in a bin based on the initial response of the user, compute the metric value in each bin, and finally average across bins. We used 21 uniformly spaced bins for this evaluation. These binned metrics are shown in Table 7. We observed two key results:

1. Activation rate increases when using modified advice. This increase is highest when using the sigmoid-like function. It is similar for both step functions.

   Additionally, note that when looking at the non-binned activation rates, the high confidence step function activation rate actually decreases relative to the baseline. This suggests that the high confidence step function advice is only used by certain groups of people (i.e., based on their confidence in the tasks), and may not be as useful depending the distribution of users. This is not the case for the sigmoid-like modification function.

2. Accuracy and confidence increase when using the modified advice. This increase is similar for the sigmoid-like function and the high confidence step function, but is lower for the low confidence step function.

Table 6: Summary of results comparing step function transforms of AI advice. "before / after" refers to before and after advice. "Confidence" refers to the confidence in the correct label (which is negative if the user responds incorrectly). All metrics are averages across our population.

AI advice	# Participants	# Observations	Activation Rate	Accuracy (before / after)	Confidence (before / after)
Baseline	25	800	0.42	69.0% / 79.2%	0.33 / 0.44
Sigmoid-like	28	895	0.54	69.9% / 82.7%	0.35 / 0.57
Step function (low confidence)	23	736	0.57	63.2% / 79.8%	0.19 / 0.39
Step function (high confidence)	24	768	0.36	70.3% / 81.5%	0.37 / 0.56

Table 7: Summary of results using binning to reduce variation based on user performance across AI advice groups. We place each human-AI interaction in a bin based on the human's initial response, and average each metric across bins.

AI advice	Activation Rate	Accuracy Delta	Confidence Delta
Baseline	0.56	19.0%	0.19
Sigmoid-like	0.77	28.5%	0.39
Step function (low confidence)	0.69	26.5%	0.29
Step function (high confidence)	0.71	29.1%	0.39

Taken together, these results suggest that the sigmoid-like function is the best choice out of the 3 functions. It has comparable performance increases to the high confidence step function but also has the highest increase in activation rate, suggesting it is more useful for a broader category of human-AI interactions.