Will We Trust What We Don’t Understand?
Impact of Model Interpretability and Outcome Feedback on Trust in AI

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Abstract

Despite AI’s superhuman performance in a variety of domains, humans are often unwilling to adopt AI systems. The lack of interpretability inherent in many modern AI techniques is believed to be hurting their adoption, as users may not trust systems whose decision processes they do not understand. We investigate this proposition with a novel experiment in which we use an interactive prediction task to analyze the impact of interpretability and outcome feedback on trust in AI and on human performance in AI-assisted prediction tasks. We find that interpretability led to no robust improvements in trust, while outcome feedback had a significantly greater and more reliable effect. However, both factors had modest effects on participants’ task performance. Our findings suggest that (1) factors receiving significant attention, such as interpretability, may be less effective at increasing trust than factors like outcome feedback, and (2) augmenting human performance via AI systems may not be a simple matter of increasing trust in AI, as increased trust is not always associated with equally sizable improvements in performance. These findings invite the research community to focus not only on methods for generating interpretations but also on techniques for ensuring that interpretations impact trust and performance in practice.

Significance Statement

Why don’t people adopt AI systems when they widely outperform humans? Understanding this phenomenon is of significant interest to computer science and social science researchers and to practitioners. It is believed that AI systems’ lack of interpretability (their inability to explain why decisions were reached) is hurting trust in these systems, though this has been understudied. We investigate whether improving AI interpretability and providing feedback on the outcome of AI decisions increases human trust in AI and human performance in AI-assisted prediction tasks. Counter to the focus on interpretability as a central driver of trust in AI, we find that outcome feedback has a greater effect on human trust and performance.
Introduction

One of the most important trends in recent years has been the growth of Big Data and predictive analytics. With advances in machine learning (ML), ML-based artificial intelligence systems can not only meet but oftentimes exceed human-level performance in a variety of domains (1–3). Yet, despite the high performance of these systems, users have not readily adopted them. This phenomenon is not a new one, as users’ reluctance to adopt algorithms into their decision making has been demonstrated over time. In a meta-analysis of 136 studies that compared algorithmic and human predictions of health-related phenomena, algorithms outperformed human clinicians in 64 studies (about 47% of the time) and demonstrated roughly equal performance in 64 studies. Human clinicians outperformed algorithms in only 8 studies—that is, about 6% of the time (4). Nonetheless, algorithms were not found to be widely used in making health-related predictions. In other studies, AI has been similarly found to not be widely used in medical settings (5), by clinical psychologists (6), in firms (7), by professional forecasters across various industries (8), and in a variety of tasks typically performed by humans (9).

Two streams of research have emerged that are relevant to this issue of AI adoption. The first focuses on understanding what factors affect user behavior and, in particular, user trust in modern AI systems and the machine learning algorithms on which they are based. This stream assesses a range of factors that could influence human interaction with and adoption of AI systems, including algorithm errors and performance accuracy (10, 11), human control over algorithmic decisions (12), whose decision-making is replaced by algorithmic decisions (13), the uncertainty inherent in the decision domain (14), algorithm transparency (15, 16), and interpretability as manipulated by varying transparency and number of features in the model (17).

The second stream focuses specifically on modern ML algorithms' lack of interpretability. Without interpretability, it is unclear which factors most influence an algorithm’s decision-making, and this lack of interpretability is thought to impact a variety of stakeholders in different ways. For example, interpretability is believed to be key to gaining users’ trust in ML systems (18–20). Interpretability can also assist developers with debugging (21); help meet legal requirements regarding a right to explanation (22); help humans detect problematic patterns in AI predictions, such as those due to covariate shift (23); and help ensure algorithmic fairness, reliability, and privacy (24). Thus, this stream of research largely focuses on technical solutions to improve interpretability, such as through post hoc, model-agnostic methods like SHAP (SHapley Additive exPlanations) and LIME (Local Interpretable Model-agnostic Explanations) (18, 25).
It is believed that the lack of interpretability could be hampering adoption of ML-based AI systems because users may not trust a system whose decision process they do not understand (26). Despite this common belief, there has been relatively little work at the intersection of these research streams. In particular, it is still unclear that improved interpretability will in fact lead to greater trust in AI systems or that increased trust is sufficient to improve AI-assisted human decision-making. One primarily observational study, focused on data scientists and ML practitioners, found that these individuals tended to overtrust and misuse interpretability tools such as SHAP (21), though this is not necessarily representative of how interpretability will affect lay users’ trust in AI. Another study focused on the layperson and assessed four different presentations of AI explanations (or interpretations within the context of our study) to understand whether they satisfy three desiderata, one of which was trust calibration (27). This study found that in a decision domain in which lay participants had low expertise, none of the explanations improved trust calibration, although in a decision domain wherein the participants had higher expertise, two of the four presentations of explanations slightly improved participants’ appropriate trust in the model. However, this study does not shed light on how the effect of interpretability would compare to other mechanisms for improving trust, such as feedback on model performance, nor does it disentangle trust in the AI system from performance in the AI-assisted prediction task, as the “trust calibration” is a composite measure of the two.

Our study seeks to understand whether and how the kinds of interpretations receiving attention from a technical standpoint affect human trust and performance in practice among laypeople. Just as “normative questions about algorithmic aversion are relevant because algorithmic aversion is empirically verifiable,” an empirical understanding of how interpretability actually affects human trust in AI systems is critical to informing further work on how to improve human trust in AI (28).

In particular, we study two levels of interpretability described in the literature, global and local interpretability (derived using the model-agnostic methods SHAP and LIME, respectively). Global interpretability clarifies which variables are “important” to the model’s decision-making in aggregate, while local interpretability clarifies which variables are “important” for a specific decision (24, 27). We also investigate how the effects of interpretability compare to those of outcome feedback, which delivers information about a prediction’s accuracy by providing the actual outcome of the predicted event. The impact of outcome feedback on trust in AI has not previously been assessed, though information about an AI system’s overall accuracy (as opposed to event-specific information like outcome feedback) has been shown to influence people’s reliance on model decisions (29) and to impact trust (10, 11). Finally, we assess how interpretability and outcome feedback affect participant performance in the prediction task to
not only understand whether these factors increase trust in AI, but if so, whether the increased trust is associated with greater accuracy in the task. We specifically ask: *How do global interpretability, local interpretability, and outcome feedback affect human trust in AI and human performance in prediction tasks?*

**Experiment Design**

We tackle our question in two web-based experiments. The experimental design and prediction task were the same across both experiments, and both experiments were implemented using the Empirica virtual laboratory platform (30). However, the user interface differed in the two experiments (see SI Figures S1 and S2) and participants were recruited from different online recruiting panels (Experiment 1: Amazon Mechanical Turk; Experiment 2: Prolific), allowing us to ensure that our results hold across panels and regardless of the specific task presentation.

In our experiments, participants (n=800 in Experiment 1; n=711 in Experiment 2) made predictions about the outcomes of speed dating events, first without and later with AI predictions. To assess the impact of model interpretability and outcome feedback on user trust and prediction accuracy, participants were randomized to one of six conditions in a between-subjects experiment design. Compensation was performance-based, as described in the SI section “Participant Compensation.”

**Prediction Task.** The task, consisting of two phases, asked participants to predict whether couples that had previously met through speed dating would want to pursue a second date.

*Phase 1* involved 12 task instances (the same instances were used for both experiments). The first two were for practice purposes, and participants were informed that the results would not be used in data analysis. These two practice task instances appeared in consistent order for all participants, while the later ten (the results of which were used for data analysis) were randomized. Each task instance presented information about one couple that met through speed dating and asked participants to predict the likelihood that the couple would want a second date. The provided information included (1) Demographics (age and race of the man and woman), (2) Ratings (the man’s and woman’s ratings of each other across six attributes: attractiveness, sincerity, intelligence, shared interests, fun, and ambition), and (3) Interest correlation (a score representing the similarity between the man’s and woman’s stated individual interests). Participants made predictions on a slider scale ranging from 0% (extremely unlikely to want a second date) to 100% (extremely likely to want a second date).
Phase 2 involved the same 12 task instances. In each of these, participants had an opportunity to revise their prior prediction from phase 1 after receiving the AI’s prediction for that couple. Similar to phase 1, participants were informed that the first two task instances were for practice purposes and only the revised predictions made in the remaining ten task instances of phase 2 would count towards their final score. Task instances in phase 2 appeared in the same order as they did in phase 1.

We chose this prediction task because it is relatable for participants and realistic in terms of how AI is used in the real world (online dating applications frequently incorporate predictive analytics). Additionally, the dataset on which this task is based, compiled by Fisman et al. (2006) (31), was also used in a related study by Yin et al. (2019) to investigate factors affecting trust in ML systems (11).

Procedures. All participants received the same information in phase 1 and the same AI predictions in phase 2. However, in phase 2, participants received varying levels of interpretability and/or outcome feedback, depending on the condition into which they were randomized. There were three interpretability levels (no interpretability, global interpretability, and local interpretability), combined with two outcome feedback levels (no feedback and with feedback), for a total of six conditions.

When interpretability was provided, it was delivered alongside the AI prediction so that participants could take it into account before making their final prediction in a given task instance. When outcome feedback was provided, it was furnished after users made their final prediction for a given task instance, as it revealed the actual outcome (whether the couple went on a second date or not). Nonetheless, because outcome feedback was provided task instance by task instance, participants could take outcome feedback from prior task instances into account before making future predictions. This format is analogous to common real-world AI interactions such as with agents like Amazon Alexa, Google Home, and Siri. In those interactions, users can observe the accuracy of the agent’s understanding of their questions and oftentimes also the accuracy of the agent’s response depending on the kind of question asked (e.g., “What is the weather going to be like today?”) prior to future interactions with the agent.

An illustrative diagram of the experimental design can be found in Figure 1.
**Figure 1. Experimental design diagram.** The experiment consisted of two phases. Phase 1 involves participants making initial predictions without AI and consists of 12 task instances, with each task instance being composed of 2 steps. In step 1, participants view information about one couple, and in step 2, participants predict how likely that couple is to want a second date. Phase 2 involves participants revising their initial predictions from phase 1 after receiving the predictions of an AI system. Phase 2 also has 12 task instances (each task instance corresponds to a task instance from phase 1), but the steps in each task instance depend on the condition to which a participant is randomized. There are six conditions that vary in the levels of interpretability and outcome feedback they provide. For all conditions, step 1 involves viewing the AI prediction. For conditions that include interpretability, this AI prediction is accompanied by either a global or local interpretation. For all conditions, step 2 involves revising the initial prediction made previously in phase 1. For conditions that include outcome feedback there is a third step that involves viewing the actual outcome (whether or not the couple went on a second date).

**Description of the Model Interpretations.** The interpretations in this experiment explained what led the AI system to make its predictions, either in aggregate (global interpretability) or for a specific prediction (local interpretability) (24). Global interpretations were extracted using SHAP (25), and local interpretations were extracted using LIME (18). The interpretations were provided as bar charts, a common way of presenting model interpretations. Furthermore, to confirm participants understood the provided interpretations, they were asked in an exit survey about the ease with which they could understand the information they were given. For additional details regarding the interpretations, see SI section “Description of Model Interpretations” and SI Figures S3 and S4. For details regarding the participants’ self-reported ease of understanding, see SI section “Self-Report Measures.”

**Trust and Performance Measures.**

*Behavioral Trust Measure.* Our measure of behavioral trust is weight of advice (WoA), a measure frequently used in the literature on trust, including trust in AI (32–34), as well as in the literature on advice taking (33, 35–37). WoA quantifies the degree to which people update their response (e.g.,
predictions made prior to seeing AI predictions) towards provided advice (the AI prediction). In our experiments, it is defined as

\[ \text{WoA} = \frac{(\text{initial prediction} - \text{final prediction})}{(\text{initial prediction} - \text{AI prediction})} \]

If \(|\text{AI prediction} - \text{initial prediction}| < 0.15\), \(\text{WoA} = \text{NA}\)

The numerator indicates how much the participant’s final and initial predictions differ. The denominator takes into account where the participants initially fall relative to the AI prediction. WoA equals 1 if the final prediction matches the AI prediction, 0.5 if the final prediction is the average of the initial and AI predictions, and 0 if the final and initial predictions are the same. WoA is less than 0 if the participant moved further away from the AI in their final prediction (“contradicting” the AI) and greater than 1 if the participant moved beyond the AI (“overshooting” the AI). Higher WoA indicates greater trust in AI, while lower WoA indicates less trust.

As noted, we dropped WoA scores when \(|\text{AI prediction} - \text{initial prediction}| < 0.15\). Because participants could only make selections in increments of 0.05 on the slider scale, it was difficult to make small revisions to match the AI (e.g., if the distance between the initial prediction and AI prediction was 0.1, this revision was difficult to make). Therefore, we interpreted predictions within 0.15 of the AI system as being equivalent to the AI prediction. The 0.15 threshold constitutes a deviation from our pre-registration (for details see SI section “Dependent Variables”). We also tested and confirmed that there are no qualitative changes to the results with thresholds of 0.05 (our pre-registered threshold), 0.1, and 0.2 (see SI section “Robustness Checks”).

**Performance Measure.** Our measure of performance is the absolute error of the participant’s final prediction, which constitutes a deviation from our pre-registration plan (see SI section “Dependent Variables”). In the context of our experiments, absolute error is calculated as follows:

\[ \text{Absolute Error} = |\text{actual value} - \text{final prediction}| \]

Wherein actual value = 1 if the couple went on a second date and 0 if the couple did not.

Absolute error can range from 0 to 1. An absolute error of 1 indicates that the participant’s final prediction was the exact opposite of the actual dating outcome (0 when the actual outcome was 1 or vice versa). An absolute error of 0 indicates that the participant’s final prediction was exactly the same as the actual outcome. Thus, an absolute error closer to 0 indicates greater accuracy, while an absolute error closer to 1 indicates less accuracy. We also measured performance using square root error and squared error (see SI section “Robustness Checks”).
Hypotheses. We predict that (1) global interpretability, local interpretability, and outcome feedback will all increase trust in AI, (2) there will be an interaction where feedback will be most effective in the absence of interpretability, and (3) global interpretability, local interpretability, and outcome feedback will all increase the accuracy of participants’ predictions, owing to the increased trust in AI (per our first hypothesis) as well as the fact that in our task AI is on average more accurate than human predictors. All hypotheses were pre-registered (AsPredicted #37908).

Results

Impact of Outcome Feedback and Interpretability on Behavioral Trust in AI. This experiment sought to assess the impact of outcome feedback and interpretability on behavioral trust in AI. Figure 2 compares the standardized (z-scored within each task instance) effect of outcome feedback, interpretability, and the interaction of these two factors on behavioral trust. Behavioral trust was assessed using the WoA metric, as described in the Trust and Performance Measures section.

Figure 2. The effect of outcome feedback, interpretability, and the interaction of these two factors on behavioral trust (WoA). Outcome feedback leads to the largest increase in WoA. Global and local interpretability also increase WoA in the combined dataset, although this is not always true for each experiment individually. There is no interaction between outcome feedback and interpretability. Experiment 1 is depicted by the blue dot, Experiment 2 by the orange triangle, and the full dataset (combining Experiments 1 and 2) by the green star.
As shown in Figure 2, outcome feedback led to the greatest and most reliable increase in behavioral trust (Experiment 1: $P < 0.001$; 95% CI = [0.163, 0.443]; Experiment 2: $P < 0.003$; 95% CI = [0.103, 0.439]). However, global and local interpretability were not observed to have a robust effect on trust (Experiment 1: global: $P < 0.038$; 95% CI = [0.009, 0.289]; local: $P < 0.059$; 95% CI = [-0.004, 0.273]; Experiment 2: global: $P < 0.298$; 95% CI = [-0.078, 0.257]; local: $P < 0.109$; 95% CI = [-0.030, 0.304]). Furthermore, the effect of interpretability on trust was modest relative to the effect of outcome feedback and not robust to different choices of $|\text{AI prediction} - \text{initial prediction}|$ thresholds in our definition of WoA (see SI section “Robustness Checks”). Additionally, there was no difference between global and local interpretability in terms of impact on trust (Experiment 1: $P < 0.838$; 95% CI = [-0.154, 0.125]; Experiment 2: $P < 0.575$; 95% CI = [-0.118, 0.214]). In contrast to our hypothesis, there was no observed interaction between outcome feedback and interpretability, meaning that feedback and interpretability did not appear to complement (or substitute) each other when provided together (Experiment 1: feedback $\times$ global: $P < 0.703$; 95% CI = [-0.237, 0.159]; feedback $\times$ local: $P < 0.757$; 95% CI = [-0.166, 0.229]; Experiment 2: feedback $\times$ global: $P < 0.684$; 95% CI = [-0.286, 0.188]; feedback $\times$ local: $P < 0.197$; 95% CI = [-0.392, 0.080]).

The finding that outcome feedback led to the greatest and most reliable increase in trust is not only counter to our hypothesis but also counter to the current focus on interpretability as a central driver of trust in AI systems. However, it is in line with a related finding that people judge humans by their intentions but judge machines by their outcomes (28). It is important to note that interpretability and intention are not the same; interpretations simply explain what factors led an AI system to reach its predictions. However, prior research shows that, in the mind of a human, the outcome of a machine’s action appears to be more important than the intention behind that action (28). This is similar to our finding that human trust in AI systems appears to be influenced more by feedback on the outcome of AI predictions than by information about the reasoning behind those predictions.

**Impact of Outcome Feedback and Interpretability on Performance Accuracy.** This experiment also sought to assess the impact of outcome feedback and interpretability on participants’ performance in the prediction task. Performance was assessed using the absolute error metric, as described in the Trust and Performance Measures section. Decreased absolute error indicates improved performance accuracy, while increased absolute error reflects the opposite.

All participants received AI predictions prior to making their own final predictions. Table 1 lists the overall change in performance (absolute error) for participants in each condition. It also specifies how
many cases in each condition demonstrated performance improvement and decrease, as well as the average changes in absolute error for these sets.

As shown in Table 1, overall performance across all conditions improved (absolute error decreased) after participants received the AI predictions. This was expected given that this experiment’s AI system was on average more accurate than the participants. The overall change in absolute error ranged from an improvement of 14.6% to an improvement of 22.1%.

Table 1. Changes in absolute error by condition. Overall performance across all six conditions improved (absolute error decreased) after receiving the AI predictions. This overall change in absolute error ranged from an improvement of 14.6% to an improvement of 22.1%. For those cases demonstrating performance improvements, the average improvement ranged from 30.7% to 44.9%. For those cases demonstrating performance reductions, the average reduction ranged from 60.8% to 73.9%. Note that cases where WoA=0 were marked as “cases with no change” in this analysis as WoA=0 indicates that the participant did not change their prediction after receiving the AI system’s prediction, meaning that there was no change in error for these cases.

| Feedback | Interpretability | Overall Change in Absolute Error | Change in Absolute Error (For those that improved) | Change in Absolute Error (For those that worsened) | Cases with No Change (WoA=0) |
|----------|------------------|----------------------------------|-----------------------------------------------|-----------------------------------------------|------------------------------|
| No       | No               | -14.6% (N=1,545)                | -30.7% (N=878; 57%)                           | +62.3% (N=330; 21%)                          | (N=337; 22%)                |
|          | Global           | -17.0% (N=1,578)                | -34.1% (N=938; 59%)                           | +60.8% (N=377; 24%)                          | (N=263; 17%)                |
|          | Local            | -15.8% (N=1,641)                | -34.5% (N=960; 59%)                           | +68.2% (N=401; 24%)                          | (N=280; 17%)                |
| Yes      | No               | -18.5% (N=1,552)                | -43.3% (N=885; 57%)                           | +71.7% (N=363; 23%)                          | (N=304; 20%)                |
|          | Global           | -22.1% (N=1,549)                | -46.7% (N=899; 58%)                           | +71.3% (N=343; 22%)                          | (N=307; 20%)                |
|          | Local            | -21.4% (N=1,557)                | -44.9% (N=912; 59%)                           | +73.9% (N=347; 22%)                          | (N=298; 19%)                |

Figure 3 compares the standardized effect of outcome feedback, interpretability, and the interaction of these two factors on performance in order to assess what impact, if any, these factors had on participant performance, beyond the effect that was attributable to the AI predictions themselves.
Figure 3. The effect of outcome feedback, interpretability, and the interaction of these two factors on performance accuracy (absolute error). Outcome feedback led to a further improvement in performance (decrease in absolute error) beyond that which was attributable to the AI predictions both in Experiment 1 and for the combined dataset, though this effect was slightly smaller and not significant for Experiment 2 individually. Neither global nor local interpretability were found to impact performance. The interaction between feedback and interpretability also did not impact performance. Experiment 1 is depicted by the blue dot, Experiment 2 by the orange triangle, and the combined dataset (combining Experiments 1 and 2) by the green star.

As shown in Figure 3, outcome feedback led to a further improvement in performance (decrease in absolute error) beyond that which was attributable to the AI predictions, although this effect was slightly smaller and not significant in Experiment 2 (Experiment 1: $P < 0.003; 95\% CI = [-0.265, -0.058]$; Experiment 2: $P < 0.369; 95\% CI = [-0.169, 0.063]$). The improvement in performance resulting from outcome feedback was consistent with our predictions.

However, contrary to our expectations, neither global nor local interpretability were found to impact performance (Experiment 1: global: $P < 0.224; 95\% CI = [-0.167, 0.039]$; local: $P < 0.369; 95\% CI = [-0.148, 0.055]$; Experiment 2: global: $P < 0.954; 95\% CI = [-0.112, 0.119]$; local: $P < 0.910; 95\% CI = [-0.108, 0.122]$). Furthermore, the interaction between feedback and interpretability was also not found to impact performance (Experiment 1: feedback × global: $P < 0.784; 95\% CI = [-0.125, 0.166]$; feedback × local: $P < 0.913; 95\% CI = [-0.153, 0.137]$; Experiment 2: feedback × global: $P < 0.203; 95\% CI = [-0.269, 0.057]$; feedback × local: $P < 0.716; 95\% CI = [-0.193, 0.133]$).
The finding that outcome feedback improved participant performance in the prediction task, while interpretability was not observed to improve performance, is in line with the previously discussed finding that outcome feedback had a more significant effect on trust in AI than did interpretability. However, it is critical to note that while outcome feedback led to improved performance, the size of this performance increase was relatively small compared to the extent to which that feedback improved behavioral trust. Similarly, interpretability was not observed to have an impact on performance in the prediction task, though it was found to increase trust in AI to some extent. This suggests that the relationship between trust in AI and performance in the prediction task may not be as direct as initially assumed. In particular, these findings do not appear to support the assumption that increased trust in AI directly leads to improvements in performance; instead, this experiment found that improved trust in AI is not always associated with equally sizable performance improvements. The noisy nature of the relationship between trust in AI and performance in the prediction task is consistent with prior work by Wang and Yin (2021) that grouped “trust calibration” into overtrust AI (following AI when it is incorrect), appropriate trust (following AI when it is not correct), and undertrust (not following AI when it is correct) (27).

**Exploratory Time-Dependent Trends**

In this experiment, participants had sequential interactions with AI, meaning that participants received AI predictions as well as interpretability and/or outcome feedback following each task instance. This raises the question of whether there exists a time-dependent trend in terms of how these factors affect trust in AI and performance in the prediction task. Exploratory analysis suggests that outcome feedback appears to impact trust and performance over time. Specifically, trust and performance appear to depend on the kinds of experiences a participant had with the AI system in prior task instances.

**Time-Dependent Trend Specific to Behavioral Trust.** Participants' initial predictions were, on average, less accurate than the AI predictions, meaning that humans would improve their performance were they to trust the AI. However, there were also instances where a participant’s initial prediction was more accurate than the AI prediction; were the humans to trust AI in those specific cases, their performance would decline. Because outcome feedback was provided after each task instance, participants knew whether following AI in prior task instances helped or hurt their performance before proceeding to subsequent task instances.

Figure 4 compares the standardized effect of three aspects of a given task instance (at time $t$) on behavioral trust in a subsequent task instance (at time $t+1$). The first factor ($Error_{AI}^{t} - error_{h}^{t}$) represents the initial difference in performance between the AI system and the human in a given task.
instance. The second factor \((WoA_t)\) represents the human’s behavioral trust in a given task instance. The third factor \((WoA_t: \text{error}^\text{Al}_t - \text{error}^\text{h}_t)\) is the interaction of the first two factors. One of the scenarios this interaction captures is where a participant’s initial prediction was more accurate than the AI prediction, but the participant revised their prediction towards the AI prediction and reduced their accuracy as a result (e.g., AI “harmed” the participant’s performance). For each factor, \(WoA_{t+1}\) is compared for the feedback group (all cases in which participants received outcome feedback, combined across both experiments) and the non-feedback group (all cases in which participants did not receive outcome feedback, combined across both experiments).

**Figure 4.** The effect of the difference in performance between the AI system and the human \((\text{error}^\text{Al}_t - \text{error}^\text{h}_t)\), the human’s behavioral trust in a given task instance \((WoA_t)\), and the interaction of these two factors \((WoA_t: \text{error}^\text{Al}_t - \text{error}^\text{h}_t)\), on trust in a subsequent task instance \((WoA_{t+1})\). For each of these factors, \(WoA_{t+1}\) is compared for the feedback group (all cases in which participants received outcome feedback, combined across both experiments) and the non-feedback group (all cases in which participants did not receive outcome feedback, combined across both experiments). For the feedback group, two effects were observed. First, the aggregate effect was that \(WoA_{t+1}\) was greater than \(WoA_t\) for the feedback group. A second effect was observed in the subset of cases where AI “harmed” the participant (reflected in the interaction term \((WoA_t: \text{error}^\text{Al}_t - \text{error}^\text{h}_t)\)). In these cases, \(WoA_{t+1}\) was reduced relative to \(WoA_t\). Neither of these two effects were observed for the non-feedback group. The feedback group is depicted by the blue dot, while the non-feedback group is depicted by the orange triangle.

As shown in Figure 4, \(WoA\) was greater at time \(t+1\) as compared to time \(t\) for the feedback group (Feedback Group: \(P < 0.001; 95\% \text{ CI} = [0.061, 0.172]\); Non-Feedback Group: \(P < 0.268; 95\% \text{ CI} = [-0.022, 0.080]\)). This suggests that overall, feedback increases trust over time, as seeing feedback for one task instance (time \(t\)) tends to increase behavioral trust in AI in the subsequent instance (time \(t+1\)).

While increased behavioral trust over time was the overall effect observed for the feedback group, a markedly different, though still time-dependent, effect was observed in cases where following the AI
“harmed” the participant (reflected in the interaction term $WoA_t : error^{AI}_t \text{ - } error^h_t$). In these cases, it was observed that $WoA_{t+1}$ was significantly reduced relative to $WoA_t$ for the outcome feedback group (Feedback Group: $P < 0.001; 95\% CI = [-0.298, -0.086]$; Non-Feedback Group: $P < 0.592; 95\% CI = [-0.069, 0.120]$). This suggests that the experience of trusting AI and having one’s performance decrease as a result leads to a loss of trust in AI in the subsequent instance. This proposed trend is in accordance with prior research that found people do not trust algorithms after observing them fail (10).

These observations that outcome feedback tends to increase trust over time in aggregate, but decrease trust after a particular negative experience, are consistent with the theory that outcome feedback impacts behavioral trust over time. These trends were only seen for the feedback group, which was expected given that the non-feedback group did not receive information about actual outcomes and thus did not know whether following AI was helping or hurting their performance over time.

**Time-Dependent Trend Specific to Performance Accuracy.** Similar time-dependent trends were observed regarding the impact of outcome feedback on performance. The factors assessed in Figure 4 are again compared in Figure 5, with Figure 5 comparing the standardized effect of these factors on performance (absolute error) at time $t+1$.

![Figure 5](image)

**Figure 5.** The effect of the difference in performance between the AI system and the human ($error^{AI}_t - error^h_t$), the human’s behavioral trust in a given task instance ($WoA_t$), and the interaction of these two factors ($WoA_t : error^{AI}_t - error^h_t$), on absolute error in a subsequent task instance ($|Error_{t+1}|$). For each of these factors, $|Error_{t+1}|$ is compared for the feedback group (all cases in which participants received outcome feedback, combined across both experiments) and the non-feedback group (all cases in which participants did not receive feedback, combined across both experiments). For both the outcome feedback and non-feedback groups, $|Error_{t+1}|$ is reduced for $WoA_t$ although the effect is very small and not significant for the non-feedback group. For the feedback group, it was also observed that absolute error at time $t+1$ was higher in the subset of cases where AI “harmed” the participant (reflected in the interaction term $WoA_t : error^{AI}_t - error^h_t$). This effect was not observed for the non-feedback group. The feedback group is depicted by the blue dot, while the non-feedback group is depicted by the orange triangle.
As shown in Figure 5, there were two observations regarding absolute error at time \( t+1 \), which can be analyzed in conjunction with the observations displayed in Figure 4.

Figure 5 suggests that \(|\text{Error}_{t+1}|\) is reduced for \( WoA_t \) for both the outcome feedback and non-feedback groups, although the effect is very small and not significant for the non-feedback group (Feedback Group: \( P < 0.001; 95\% \ CI = [-0.272, -0.152] \); Non-Feedback Group: \( P < 0.036; 95\% \ CI = [-0.124, -0.005] \)). Thus, it appears that when participants trust AI in one task instance, they tend to have smaller errors (improved performance) in the next instance, an effect that is stronger when feedback is provided. When analyzed in conjunction with Figure 4, this suggests that when participants in the feedback group trust AI in one task instance, trust increases even further in the next instance (Figure 4), and this increase in trust is associated with a performance improvement (Figure 5).

Figure 5 also suggests that, for the outcome feedback group, \(|\text{Error}_{t+1}|\) is increased for the interaction term \( WoA_t : error_{t, AI}^A - error_{t, h}^B \) (Feedback Group: \( P < 0.001; 95\% \ CI = [0.266, 0.494] \); Non-Feedback Group: \( P < 0.053; 95\% \ CI = [-0.001, 0.222] \)). As such, it appears that if trusting AI “harms” a participant in one task instance, error increases in the next task instance. In this way, Figures 4 and 5 together suggest that after AI “harms” a participant, trust decreases in the next instance (Figure 4), and this loss of trust is associated with reduced future performance (Figure 5). These observations are robust to other operationalizations and performance measures (see SI section “Robustness Checks”).

Taken together, these exploratory analyses suggest that outcome feedback has two time-dependent effects: it generally increases trust and performance over time, but can sometimes reduce trust and performance. Specifically, trust in AI increases over time when participants observe AI performance over time. At the same time, there is a conundrum tied to observing AI performance. Because AI systems and humans make different types of errors, AI can at times be more erroneous than human decision-makers even though it outperforms humans on average. We observe that when humans trust AI but that trust backfires (i.e. AI performs worse than the human in a particular instance), then trust in AI drops in subsequent task instances. This drop in trust hurts the human’s future performance and limits humans from fully extracting the potential value of AI decision support. Research that specifically studies these time-dependent effects, as well as research that seeks to understand the relationship between trust in AI and performance in prediction tasks, would be important extensions of the literature, among others discussed below.
Discussion

This paper applies behavioral science research methods to the study of AI systems, and thereby contributes directly to the emerging machine behavior research field, which Rahwan et al. (2019) argues is an overarching and essential area of study given algorithms’ ubiquity, their complexity and opacity, and their potential effects on humanity (38). This experiment found that interpretability, an intervention that gets significant attention and is technically challenging to provide, may be less effective at improving trust as compared to outcome feedback. This is counter to the current focus on interpretability as one of the central drivers of human trust in AI systems, though it is in line with prior research by Hidalgo et al. (2021), which finds that people judge machines by their outcomes, but judge humans by their intentions (28). Our experiment also suggests that augmenting human performance via AI may not be a simple matter of increasing trust in AI, as increases in trust may not always be followed by improvements in human performance. Taken together, these findings have significant implications for AI product design and future research in this space. In particular, they indicate that interpretations alone may not be sufficient to solve challenges related to user trust in AI products, while also opening the door for product designers to consider implementing features other than interpretability as methods of increasing trust in AI products. In addition, these findings invite the research community to bring additional attention to why the interpretations presented in this experiment had a less significant impact on trust than was hypothesized. For example, could specific presentations of interpretability, decision-making contexts, or user-specific factors affect the impact of interpretability on trust and performance in practice? Further thoughts on these areas of future research are provided below.

First, while this experiment assesses the impact of interpretability on trust and performance, and studies both global and local interpretability, it only looks at one presentation of each form of interpretability. That is, the interpretations in this experiment were always presented as lists of factors that the AI system considered important in making its decision, along with the magnitude of importance (and, for local interpretability, information on whether the factor had a positive or negative effect on the couple’s chances of going on a second date). However, interpretability could also be presented in other ways. For example, one could instead present only the most important factors, focus on abnormal explanations for the decision, or highlight what would “need to change (in the input) so that the ML prediction/decision (output) would also change,” referred to as a “contrastive” or “counterfactual” explanations (20). These and other methods are described by Carvalho et al. (2019) and are based on research by Breiman (2001), Kahneman and Tversky (1982), and Lipton (1990), respectively (20, 39–41). In fact, Wang and Yin (2021) assessed the impact of four different presentations of explanations, finding that two types
(counterfactuals and nearest neighbors) did not improve trust calibration, while the other two (feature importance and feature contribution, which are related to our study’s presentations of global and local interpretability, respectively) did have a slight impact on trust calibration, but only in a decision domain wherein the participants had higher expertise (27). However, because “trust calibration” in that experiment is a composite measure of trust and performance, it is difficult to disentangle trust in the AI system (following AI) from performance (following AI when one should versus when one shouldn’t). This area of research regarding how to present interpretations such that they are most beneficial is highly complex and deserves additional attention, especially given the broader context in which interpretations and outcome feedback might exist in practice. For example, interpretability may have a role to play in terms of ensuring fairness, reliability, and privacy in algorithms, among other uses (24). Similarly, while outcome feedback can be provided in situations where the actual outcome is immediately observable, there are also many situations where outcomes are not observable in a timely fashion (e.g., predictions for events in the distant future such as the risk of developing a disease). In light of this and the importance interpretability has for purposes beyond user trust, as well as the fact that outcome feedback, while effective at increasing trust, is not always possible to provide, we believe that the literature needs to focus as much on how to design AI interfaces and present interpretations as it has on techniques for generating interpretations.

A second area of research centers around how AI literacy interacts with factors intended to increase trust in AI, such as interpretability and outcome feedback. Participants’ past experiences with AI, or their lack of exposure to AI, could be influencing the impact of interpretability and/or feedback on their trust behavior. For example, our experiment focused on the general public and found that interpretability did not lead to robust improvements in trust, while (21) found that data scientists and ML practitioners tended to overtrust and misuse interpretability tools. Further research on how AI literacy or expertise affects AI trust would provide insight into how to tailor AI product features to specific customers and markets.

Third, this experiment only involves one context, in which participants (and the AI system) are making predictions about speed dating couples. Broadly speaking, this can be described as a context in which the people the decisions are about (the speed dating couples) are different from those choosing whether or not to use the AI system (the participants). This is not an uncommon application context for AI (e.g., loan officers consulting AI for loan approvals, doctors consulting AI for diagnoses, judges consulting AI to make sentencing decisions, etc.). However, there is another type of context in which the people the decisions are about also have a say in whether or not to use AI (e.g., an individual choosing whether or not to follow AI-generated recommendations of products or media for that individual to consume). It is
plausible that this change in context may lead to different results about the relative impact of global vs. local interpretability. For example, an individual may be relatively indifferent between aggregate (global) interpretations versus interpretations about a specific person (local interpretations) unless that person is them. It would therefore be worthwhile to assess the value of global and local interpretability in contexts where the people that the AI predictions are about have real decision-making power regarding whether and how much to trust the system.

Additionally, as discussed previously, exploratory analysis suggests that outcome feedback leads to an overall increase in trust and performance over time, while also reducing trust and performance in some cases. Additional research regarding these apparent time-dependent effects would help clarify how feedback results in the impacts on trust and performance observed in this experiment.

Finally, despite the fact that this experiment was focused on interpretability and outcome feedback, one critical finding was not about interpretability or outcome feedback at all, but was instead that increased trust in AI does not always lead to equally significant improvements in human performance. Thus, any research, even outside the context of interpretability or outcome feedback, that can shed light on the relationship between trust in AI and performance in a prediction task would be highly important. Greater clarity regarding when and how to increase trust such that trust improvements translate into performance improvements will help work towards the end goal of not just greater adoption of AI systems, but greater impact from these systems.

**Materials and Methods**

**Pre-registration Statement.** The study was reviewed and approved by the Institutional Review Board and Human Research Protections Program at the University of Pennsylvania (protocol #834692). All participants provided explicit consent to participate in this study, and the IRB approved the consent procedure. Our experimental design, sample size, and analyses (regarding the impact of outcome feedback and interpretability on behavioral trust in AI and performance in the prediction task) were pre-registered before the collection of the data (pre-registration: https://aspredicted.org/hg5w6.pdf). All other analyses are exploratory.

**Training Process for the AI System.** We used the ensemble tree model XGBoost (eXtreme Gradient Boosting) to determine the AI predictions. This model is known for its superior performance in handling tabular data and is popular in the literature (42, 43). We first used downsampling to correct a class imbalance problem inherent in our dataset, and then trained the model using 5-folds cross validation. The
model’s accuracy was about 79%. For additional details, including with regard to how we addressed class imbalance, see SI section “AI System Training.”

**Statistical Analysis.** Because each participant completed the twelve task instances, of which the last ten were used for data analysis, we conducted tests for differences across conditions at the task level. We modeled the data using a generalized linear mixed model for each outcome (e.g., trust, performance) with a random effect for the participant. These models account for the nested structure of the data. All statistical tests were two-tailed (as per our pre-registration). For additional details, see SI section “Normalization and Statistical Analysis.”

**Standardized Coefficients.** To enable meaningful comparisons of effect sizes across different condition groups while controlling the effects of varying levels of difficulty among task instances, we standardize outcome metrics (e.g., trust, performance) within each task instance. The standardized value of measurement X, measured for task instance i, is defined as

\[
X_{i,\text{standardized}} = \frac{X_i - \mu_X}{\sigma_X}
\]

wherein \(\mu_X\) is defined as the mean of X across all instances of the task (for all condition groups), and \(\sigma_X\) is the SD.

**Data Availability.** The replication data and code are available at: https://doi.org/10.7910/DVN/VXD9J2. The experiment was developed using the Empirica (https://empirica.ly/) platform, an open-source “virtual lab” framework and platform for running multiplayer interactive experiments and games in the browser (30). The source code for the “Speed Dating Match Prediction” task can be found at https://github.com/amaatouq/speed_dating_human_ai.
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Supplementary Information for:

Impact of Model Interpretability & Outcome Feedback on Trust in AI

This file includes:

- Supplementary text
- Supplementary figures and tables
- References for SI reference citations
1. Access to data, code, and analysis plan

All of the data, analysis code, and the pre-registration plan are publicly available at (pre-registration: https://aspredicted.org/hg5w6.pdf; data and analysis code: https://doi.org/10.7910/DVN/VXD9J2). The study was reviewed and approved by the Institutional Review Board and Human Research Protections Program at the University of Pennsylvania (protocol #834692). The experiment was developed using the Empirica (https://empirica.ly/) platform, an open-source “virtual lab” framework, and a platform for running multiplayer interactive experiments and games in the browser (Almaatouq et al. 2021). The source code for the “Speed Dating Match Prediction” task can be found at https://github.com/amaatouq/speed_dating_human_ai.

2. Details of Experimental Setup

**Speed dating prediction task.** The task consisted of two phases. In phase 1, participants received information about couples that met through speed dating and made predictions about the likelihood that each couple would pursue a second date. In phase 2, participants had a chance to revise the predictions they made in phase 1 after receiving the AI system’s predictions for each couple. This prediction task was designed to expose the extent to which participants update their predictions towards the AI system’s prediction. It was also designed to expose the accuracy of participants’ predictions and whether accuracy improved after participants received the AI system’s predictions. Examples of phase 1 and phase 2 task instances (for both experiments 1 and 2) are provided in Figures S1 and S2 below.

![Figure S1. Phase 1 task instance](image1)

![Figure S2. Phase 2 task instance](image2)

**Experiment 1**

**Experiment 2**
Experiment 1

If you want to modify your results, select the value you want, otherwise please reselect the same value.

| Matching ID | 1049 | Interests Correlation | 0.08 |
|-------------|------|------------------------|------|
| Women       |      |                        |      |
| Race        | European/Caribbean-American | Race | European/Caribbean-American |
| Age         | 21   | Age                    | 28   |
| Attractive  | 8    | Attractive             | 6    |
| Sincere     | 5    | Sincere                | 0    |
| Intelligent | 7    | Intelligent            | 0    |
| Fun         | 7    | Fun                    | 0    |
| Ambitious   | 9    | Ambitious              | 10   |
| Shared Interests | 9 | Shared Interests | 10 |

Make your final prediction:

Experiment 2

Your previous prediction was '61%'
A.I. predict the matching probability of this case as '76%'

The A.I. algorithm calculated the matching probability based on the importance of the variables below.

Figure S2. Phase 2 task instance. Examples of a task instance in phase 2 (shown with global interpretability) for experiments 1 and 2.
**Design of experiment.** Phase 1 of the task was consistent across participants, meaning that all participants received the same information about the same couples, and all participants were asked to make predictions about the likelihood that each couple would pursue a second date. In phase 2, participants were randomized into 6 different condition groups. All conditions involved providing participants with the AI system’s prediction for each couple, but the conditions varied on the basis of the levels of interpretability and outcome feedback that they provided. Participants were not informed about the interpretability and outcome feedback levels that other participants received. This experimental design allowed us to evaluate whether providing interpretability and/or outcome feedback results in participants moving closer to the AI prediction than they do after receiving AI predictions alone. It also allowed us to evaluate whether providing interpretability and/or outcome feedback led to any additional change in the accuracy of participants’ predictions, beyond the changes in accuracy that were attributable to the AI predictions themselves.

The six condition groups are as follows:

1) No interpretability + No feedback  
2) Global interpretability + No feedback  
3) Local interpretability + No feedback  
4) No interpretability + Feedback  
5) Global interpretability + Feedback  
6) Local interpretability + Feedback

Examples of global interpretability, local interpretability, and outcome feedback (as presented in experiment 1 and experiment 2) are provided in Figures S3, S4, and S5 below.

![Experiment 1](image1)

**Experiment 1**

The A.I. algorithm calculated the matching probability based on the importance of the variables below.

- Woman’s Fun
- Man’s Attractive
- Woman’s SharedInterests
- Woman’s Attractive
- Man’s SharedInterests
- Man’s Fun
- Woman’s Race
- Man’s Age
- Woman’s Ambitious
- Man’s Intelligent
- Woman’s Intelligent
- Man’s Ambitious
- Interests Correlation
- Woman’s Age
- Woman’s Sincere
- Same Race
- Man’s Race
- Man’s Sincere

![Experiment 2](image2)

**Experiment 2**

How did the AI System make this prediction? It determined that some factors are more important than others in whether a given couple wants a second date. This relative importance of factors is not specific to any one couple.

![Figure S3. Global Interpretability](image3)

**Figure S3. Global Interpretability.** Examples of global interpretability for experiments 1 and 2.
Participant recruitment. We conducted two experiments which were conceptual replications of each other with different sets of participants. The design of both experiments was identical and participants performed the exact same prediction task (described in the above sections “Speed Dating Prediction Task” and “Design of Experiment”). However, the user-interface differed significantly in the two experiments and participants were recruited from different online recruiting panels (Experiment 1: Amazon Mechanical Turk; Experiment 2: Prolific), allowing us to assess whether our results held true with different sets of participants and regardless of the presentation of the task. All participants in both experiments provided explicit consent to participate, and the Institutional Review Board and Human Research Protections Program at the University of Pennsylvania approved the consent procedures. Details about participant recruitment for each of the two experiments are described below:
Experiment 1: 800 participants were recruited across 4 days from Amazon Mechanical Turk by posting a HIT for the experiment, entitled “Predict the speed-dating outcomes and get up to $6 (takes less than 20 min)”. Participants were required to be at least 18 years of age. To ensure adequate attention on the part of participants, basic attention checks were conducted that were not related to the content of the experiment. Participants that did not pass these attention check questions were not allowed to proceed to the experiment.

Experiment 2: 711 participants were recruited across 4 days on Prolific by posting a study entitled “Predict the speed-dating outcomes and get up to $6 (takes less than 20 min).” Participants were required to be at least 18 years of age. Instead of the basic attention check questions used in Experiment 1, this experiment’s attention checks involved substantive questions related to the instructions of the task in order to ensure adequate comprehension of the task itself. These attention check questions were presented in a multiple-choice format, and participants who answered a question incorrectly were told which question was incorrect and were asked to try again until all questions were answered correctly.

Participant compensation. In both Experiment 1 and Experiment 2, the payment participants received was dependent on their performance in the task. In Experiment 1, participants received $1 in base pay plus up to $5 of performance-based bonuses. In Experiment 2, participants received $2 in base pay plus up to $5 of performance-based bonuses. The higher base pay in Experiment 2 was due to a base pay requirement of Prolific. The formula used to calculate participant pay was the same for both experiments and is detailed below:

\[
\text{base payment} + 0.5 \times \sum_{i=1}^{N} 1 - (\text{actual value} - \text{revised prediction})^2
\]

Where:
- \text{base payment} = \$1 in Experiment 1 and \$2 in Experiment 2
- \text{N} = \text{number of prediction rounds}
- \text{actual value} = 1 \text{ if the couple went on a second date} \& 0 \text{ if the couple didn’t go on a second date}

MTurk Worker IDs and Prolific IDs were automatically collected and participant data was linked to the IDs for the purposes of participant compensation. Because our study required an interactive experiment system and an incentive compatible system, and because it is currently not possible to create an incentive compatible interactive experiment entirely through MTurk or Prolific, we created our own experiment system that works with MTurk and Prolific. As such, our system needed to collect MTurk Worker IDs and Prolific IDs and link these IDs with participant data in order to calculate compensation for each
participant, as compensation was tied to performance in the task. IDs were only used for payment purposes, were deleted after payments were successfully delivered, and were not used in data analysis. The need to collect Mturk Worker IDs/Prolific IDs and link them to participant data was disclosed to and approved by the Institutional Review Board at the University of Pennsylvania.

**AI System Training.** The algorithm used to determine the AI predictions in this experiment was the ensemble tree model XGBoost (eXtreme Gradient Boosting). This model is known for its superior performance in handling tabular data and is popular in the literature (Chen and Guestrin 2016, Dhaliwal et al. 2018). Training the model involved first correcting a class imbalance problem inherent in our dataset. Specifically, our dataset had two classes (“match,” meaning the couple went on a second date, and “no match,” meaning the couple did not go on a second date). The ratio of “match” to “no match” cases was about 1:4.63 (total observations of 1040 and 4822, respectively). Because there were a significantly higher number of “no match” cases to “match” cases, models would tend to classify the prediction results into the majority class (the “no match” class). Down sampling was used to ensure an equal number of cases in each class (specifically, we randomly sampled 1040 of the 4822 “no match” cases to ensure a 1:1 ratio of “match” to “no match” cases). The model was then trained using 5-folds cross validation. Input data included demographics of each man and each woman, their ratings of the partners they met while speed dating, and each couple’s interest correlation score. The task was binary classification, with output data of 1 (match) or 0 (no match). The model’s accuracy was about 79%. After the model was trained, interpretations were extracted.

**Description of Model Interpretations.** Our definition of interpretability was not limited to information from inherently interpretable models. That is, our use of the term interpretability includes post-hoc explanations derived from otherwise opaque models using model-agnostic methods. Specifically, global interpretations in this experiment were extracted using the model-agnostic method SHAP (Lundberg and Lee 2017) while local interpretations were extracted using the model-agnostic method LIME (Ribeiro et al. 2016). Global interpretations clarify which factors the model considers most important in aggregate, across all its predictions, while local interpretations clarify which factors the model considers most important in making each specific prediction (Molnar 2019). For examples of the user interface of the global and local interpretations see SI Figures S3 and S4.
3. Details of Analysis

Independent Variables. The independent variables in this experiment are the two factors that we varied in phase 2 of the experiment: interpretability and outcome feedback. Interpretability refers to an AI system’s ability to make clear to users the factors that led certain predictions to be made. Outcome feedback refers to information users receive regarding the accuracy of a prediction. Both are categorical variables, and in these experiments interpretability consists of three categories and outcome feedback consists of two categories, as described below:

Interpretability Categories:
1) No Interpretability: The AI system’s prediction was provided on its own, without an associated explanation of the factors driving this prediction.
2) Global Interpretability: The AI system’s prediction was provided alongside an explanation of the factors that the AI system considers most important in aggregate, across all predictions.
3) Local Interpretability: The AI system’s prediction was provided alongside an explanation of the factors that the AI system considers most important in that specific case (not across all predictions in aggregate).

Outcome Feedback Categories:
1) No Outcome Feedback: Even after a final prediction was made, no feedback was provided regarding the ground truth (e.g., whether or not the couple actually went on a second date). As such, participants were not able to assess the accuracy of their own final prediction or of the AI system’s prediction.
2) Outcome Feedback: After a final prediction was made in a given task instance, feedback was provided regarding the ground truth (e.g., participants were told whether or not the couple actually went on a second date). Because outcome feedback was provided task instance by task instance, participants were able to assess the accuracy of their own prediction and the AI prediction prior to moving on to subsequent task instances.

Dependent Variables. The two dependent variables in this experiment are behavioral trust and performance accuracy. There is one primary measure for each of these two dependent variables, as well as additional measures that serve as robustness checks. The primary measures for behavioral trust and performance accuracy, as well as deviations from our pre-registration plan that relate to each measure, are discussed below.
Behavioral Trust: The primary measure of behavioral trust is Weight of Advice (WoA), which quantifies the degree to which people update their response (e.g., predictions made before seeing the AI prediction) toward advice they are given (the AI prediction). In our experiments, it is defined as:

\[ WoA = \frac{(\text{initial prediction} - \text{final prediction})}{(\text{initial prediction} - \text{AI prediction})} \]

If \(|\text{AI prediction} - \text{initial prediction}| < 0.15\), WoA = NA

As noted above, we dropped the WoA scores in instances where \(|\text{AI prediction} - \text{initial prediction}| < 0.15\). This 0.15 threshold constitutes a deviation from our pre-registration plan, as we originally intended to use the threshold of 0.05. The original reason for having a threshold and dropping WoA scores when \(|\text{AI prediction} - \text{initial prediction}|\) was below that threshold is because WoA is a less meaningful measure of behavioral trust in those situations. Because WoA is about the degree to which participants update their predictions toward the AI prediction, it is less meaningful in contexts where the participant’s initial prediction was already nearly the same as the AI prediction. We originally set the threshold to 0.05 because of the nature of the slider scale on which participants made their predictions. Participants could make selections in increments of 0.05, so we felt that cases where initial predictions were within 0.05 of the AI prediction should be dropped, but that cases where initial predictions were at a greater distance ( > 0.05) from the AI prediction should be kept. However, we deviated from this plan and raised the threshold to 0.15 because we realized that while participants could make selections in increments of 0.05, it was nonetheless difficult to make very small changes on the slider scale (e.g., if the distance between the initial prediction and AI prediction was 0.1, this revision was difficult to make). As such, we interpreted initial predictions within 0.15 of the AI system as being effectively equivalent to the AI prediction, and chose to drop these cases. As robustness checks, we also tested other thresholds in addition to 0.15, including 0.05 (our pre-registered threshold), 0.1, and 0.2. These robustness checks are described later in this document (in the “Robustness Checks” section). The primary behavioral trust measure, WoA, is interpreted and described in detail in the main text (“Trust and Performance Measures” section).

Performance: The primary measure of performance is the absolute error of the participant’s final prediction. In the context of our experiments, absolute error is calculated as follows:

\[ \text{Absolute Error} = |\text{actual value} - \text{final prediction}| \]

Where actual value = 1 if the couple went on a second date & 0 if the couple didn’t go on a second date

The use of absolute error as the primary performance measure constitutes a deviation from our pre-registration plan. Originally, we planned to use the area under the ROC curve (ROC AUC) as the primary
performance measure. The reason for the deviation is that we originally planned on conducting participant level analysis (on which ROC AUC is based), but instead decided to conduct task instance level analysis (on which error measures are based). This change from participant level to task instance level analysis had multiple benefits in the context of our experimental design. First of all, because there were only ten task instances for each participant (the first two of the twelve total task instances were for practice purposes), measuring performance at the participant level was not particularly stable or meaningful. Getting an accurate measure of performance at the participant level would have required a significantly greater number of task instances per participant. As such, given the relatively small number of task instances per participant, conducting analysis at the level of individual task instances was more meaningful. Furthermore, task instance level analysis allows for greater understanding of the context surrounding specific behaviors, as well as allows us to understand how behavior changed over the series of task instances in the experiment. This change from participant level to task instance level analysis led to the change in performance measure, as ROC AUC is based on participant level analysis, while absolute error applies to task instance level analysis. ROC AUC was still calculated as a robustness check, as were squared error and square root error. These robustness checks are described below (under “Robustness Checks”). The primary performance measure, absolute error, is interpreted and described in detail in the main text (“Trust and Performance Measures” section).

Robustness Checks. Robustness checks for the results presented in the main text are described below, under the following sections “Behavioral Trust,” “Performance,” and “Time-Dependent Trends.”

Behavioral Trust: As described previously, our primary behavioral trust measure (WoA) involved dropping WoA scores when \( |AI\ prediction - initial\ prediction| < 0.15 \). In addition to the threshold of 0.15, three other thresholds (0.05, 0.1, and 0.2) were used as robustness checks. The results of these robustness checks are displayed in Figure S6 and Table 1 below. As shown in Figure S6 and Table 1, the findings from these robustness checks are consistent with our main findings that outcome feedback led to the greatest and most reliable increase in behavioral trust, while interpretability did not lead to a robust increase in trust. There were also no differences between global and local interpretability, and no interaction between outcome feedback and interpretability, in terms of their impacts on trust.
Figure S6. Robustness checks regarding the impact of outcome feedback and interpretability on behavioral trust. In order to assess the robustness of our primary result, Weight of Advice was calculated using three additional thresholds (0.05, 0.10, and 0.20). The results of these robustness checks are consistent with our main findings.
Table 1. Statistics for the robustness checks regarding the impact of outcome feedback and interpretability on behavioral trust. In order to assess the robustness of our primary result, Weight of Advice was calculated using three additional thresholds (0.05, 0.10, and 0.20). For each threshold, the p-values and confidence intervals for each factor are listed. The results of these robustness checks are consistent with our main findings.

| Y | Exp | Factors | Threshold = 0.05 | | | Threshold = 0.10 | | | Threshold = 0.20 | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | P-value | CI Lo | CI Hi | P-value | CI Lo | CI Hi | P-value | CI Lo | CI Hi |
| | | Feedback | 0.000 | 0.127 | 0.327 | 0.000 | 0.110 | 0.357 | 0.000 | 0.161 | 0.468 |
| | | Global | 0.268 | -0.043 | 0.156 | 0.122 | -0.026 | 0.220 | 0.084 | -0.018 | 0.289 |
| | | Local | 0.092 | -0.014 | 0.185 | 0.158 | -0.034 | 0.211 | 0.110 | -0.028 | 0.276 |
| | | Feedback×Global | 0.711 | -0.114 | 0.168 | 0.780 | -0.149 | 0.199 | 1.000 | -0.217 | 0.217 |
| | | Feedback×Local | 0.489 | -0.191 | 0.091 | 0.581 | -0.125 | 0.224 | 0.749 | -0.181 | 0.251 |
| | 1 | Feedback | 0.012 | 0.034 | 0.276 | 0.003 | 0.083 | 0.397 | 0.002 | 0.107 | 0.466 |
| | | Global | 0.454 | -0.074 | 0.166 | 0.586 | -0.113 | 0.200 | 0.280 | -0.080 | 0.277 |
| | | Local | 0.292 | -0.055 | 0.184 | 0.392 | -0.088 | 0.223 | 0.053 | -0.002 | 0.353 |
| | | Feedback×Global | 0.627 | -0.212 | 0.128 | 0.429 | -0.310 | 0.132 | 0.823 | -0.281 | 0.224 |
| | | Feedback×Local | 0.154 | -0.292 | 0.046 | 0.473 | -0.301 | 0.139 | 0.195 | -0.417 | 0.058 |
| | 2 | Feedback | 0.000 | 0.120 | 0.267 | 0.000 | 0.138 | 0.335 | 0.000 | 0.185 | 0.419 |
| | | Global | 0.158 | -0.020 | 0.126 | 0.149 | -0.026 | 0.170 | 0.048 | 0.001 | 0.235 |
| | | Local | 0.041 | 0.003 | 0.149 | 0.114 | -0.019 | 0.176 | 0.013 | 0.032 | 0.264 |
| | | Feedback×Global | 0.904 | -0.110 | 0.097 | 0.687 | -0.167 | 0.110 | 0.870 | -0.179 | 0.152 |
| | | Feedback×Local | 0.106 | -0.188 | 0.018 | 0.866 | -0.151 | 0.127 | 0.480 | -0.224 | 0.105 |
| 1+2 | 1 | Feedback | 0.001 | -0.236 | -0.060 | 0.004 | -0.232 | -0.043 | 0.005 | -0.278 | -0.050 |
| | | Global | 0.757 | -0.101 | 0.073 | 0.447 | -0.130 | 0.057 | 0.398 | -0.163 | 0.065 |
| | | Local | 0.815 | -0.097 | 0.076 | 0.673 | -0.113 | 0.073 | 0.365 | -0.164 | 0.060 |
| | | Feedback×Global | 0.812 | -0.138 | 0.108 | 0.763 | -0.153 | 0.112 | 0.837 | -0.178 | 0.144 |
| | | Feedback×Local | 0.777 | -0.106 | 0.141 | 0.800 | -0.150 | 0.115 | 0.803 | -0.180 | 0.139 |
| | 2 | Feedback | 0.013 | -0.228 | -0.026 | 0.110 | -0.216 | 0.022 | 0.613 | -0.164 | 0.097 |
| | | Global | 0.602 | -0.128 | 0.074 | 0.885 | -0.128 | 0.110 | 0.714 | -0.154 | 0.105 |
| | | Local | 0.939 | -0.104 | 0.097 | 0.932 | -0.123 | 0.113 | 0.434 | -0.180 | 0.077 |
| | | Feedback×Global | 0.605 | -0.179 | 0.104 | 0.446 | -0.233 | 0.102 | 0.216 | -0.298 | 0.067 |
| | | Feedback×Local | 0.796 | -0.123 | 0.160 | 0.868 | -0.153 | 0.181 | 0.569 | -0.235 | 0.129 |
| | 1+2 | Feedback | 0.000 | -0.205 | -0.072 | 0.001 | -0.186 | -0.049 | 0.011 | -0.183 | -0.024 |
| | | Global | 0.552 | -0.086 | 0.046 | 0.493 | -0.092 | 0.044 | 0.315 | -0.120 | 0.039 |
| | | Local | 0.833 | -0.073 | 0.059 | 0.714 | -0.080 | 0.055 | 0.213 | -0.128 | 0.028 |
| | | Feedback×Global | 0.592 | -0.119 | 0.068 | 0.399 | -0.138 | 0.055 | 0.307 | -0.170 | 0.054 |
| | | Feedback×Local | 0.709 | -0.075 | 0.111 | 0.949 | -0.099 | 0.093 | 0.522 | -0.147 | 0.075 |
Performance: In addition to the primary performance measure of absolute error, three additional measures were used as robustness checks, including squared error, square root error, and the area under the ROC curve. In our experiments, these three measures were calculated in the following way:

Squared Error = \((actual\ value - revised\ prediction)^2\)

Square Root Error = \(\sqrt{(actual\ value - revised\ prediction)}\)

ROC AUC: ROC AUC measures the two-dimensional area underneath the ROC curve. The ROC curve is a graph representing the performance of a classification model at all thresholds. This curve plots two parameters: True Positive Rate (TPR) on the y-axis and False Positive Rate (FPR) on the x-axis. TPR can be computed as \({(True\ Positive)/(True\ Positive + False\ Negative})\}. FPR is computed as \({(False\ Positive)/(False\ Positive + True\ Negative})\}. True and false indicate the real value in the classification task. For example, in our experiment, true and false mean ‘match’ and ‘no match’, respectively. Positive and negative are related to the participant’s prediction (when the participant predicts “match” it is positive, and when the participant predicts “no match” it is negative).

Results for these robustness checks are displayed in Figure S7 and Table 2 below. As shown in Figure S7 and Table 2, the results for squared error and square root error are directionally consistent with our main findings that feedback increases performance (in experiment 1 and in the combined dataset), though neither interpretability nor the interaction between feedback and interpretability impact performance. While the results for squared error and square root error are directionally consistent with these findings, the size of the impact is smaller for squared error and larger for square root error due to the way these measures are calculated. Specifically, squared error tends to amplify the effect of large errors, while square root error minimizes the effect of large errors. Results from our experiment suggest that outcome feedback increased participants’ tendency to make large errors (by leading participants to make more extreme predictions, sometimes “contradicting” and sometimes “overshooting” the AI advice), which has resulted in a smaller increase in performance seen in the squared error measurement and a larger increase in performance seen in the square root error measurement (as compared to the primary measure of absolute error).

With regards to the ROC AUC measure, it is important to note that ROC AUC does not measure performance by measuring error, meaning that the direction of the ROC AUC measure is reverse to the error measures (higher ROC AUC indicates improved performance, whereas higher error indicates
decreased performance). Furthermore, a critical difference between ROC AUC and measures of error is that ROC AUC is calculated at the level of participants, as opposed to at the level of individual task instances. As a result, ROC AUC is an unstable measure of performance in this experiment, as shown in Figure S7 and Table 2. This is due to the relatively small number of task instances in our experiment. Because there were only ten task instances for each participant (the first two of the twelve total task instances were for practice purposes), measuring performance at the participant level was not particularly stable or meaningful. Getting an accurate measure of performance at the participant level would have required a significantly greater number of task instances per participant. As such, despite pre-registering ROC AUC as our performance measure, we instead used absolute error as the primary performance measure (with squared error and square root error as the main robustness checks).

Figure S7. Robustness checks regarding the impact of outcome feedback and interpretability on performance. Squared error, square root error, and ROC AUC were used to assess the robustness of our primary result (calculated using absolute error). The results for squared error and square root error are directionally consistent with our main findings, though the size of the impact is smaller for squared error and larger for square root error due to the way these measures are calculated. The results for ROC AUC were unstable. ROC AUC measures performance at the participant level instead of at the task instance level, and this turned out to be an unstable way to measure performance in this experiment given the relatively small number of task instances in our experiment.
Table 2. Statistics for the robustness checks regarding the impact of outcome feedback and interpretability on performance. Squared error, square root error, and ROC AUC were used to assess the robustness of our primary result (calculated using absolute error). For each measure the p-values and confidence intervals for each factor are listed. The results for squared error and square root error are directionally consistent with our main findings, while the results for ROC AUC are unstable as ROC AUC measures performance at the participant level, not at the task instance level.

| Exp | Factors         | Squared Error |          |          |          |          |          |          |          |          |          |          |
|-----|-----------------|---------------|----------|----------|----------|----------|----------|----------|----------|----------|----------|----------|
|     |                 | P-value | CI Lo | CI Hi |                | P-value | CI Lo | CI Hi |                | P-value | CI Lo | CI Hi |
| 1   | Feedback        | 0.277    | -0.187 | 0.054 |                | 0.000   | -0.322 | -0.117 |                | 0.030   | 0.026 | 0.509 |
|     | Global          | 0.371    | -0.175 | 0.065 |                | 0.292   | -0.157 | 0.047 |                | 0.079   | -0.025 | 0.455 |
|     | Local           | 0.813    | -0.134 | 0.105 |                | 0.254   | -0.160 | 0.042 |                | 0.209   | -0.087 | 0.395 |
|     | Feedback×Global | 0.862    | -0.185 | 0.155 |                | 0.554   | -0.101 | 0.189 |                | 0.631   | -0.424 | 0.257 |
|     | Feedback×Local  | 0.517    | -0.226 | 0.113 |                | 0.611   | -0.107 | 0.182 |                | 0.528   | -0.451 | 0.231 |
| 2   | Feedback        | 0.294    | -0.058 | 0.191 |                | 0.020   | -0.275 | -0.024 |                | 0.110   | -0.468 | 0.048 |
|     | Global          | 0.982    | -0.123 | 0.125 |                | 0.807   | -0.109 | 0.140 |                | 0.249   | -0.409 | 0.106 |
|     | Local           | 0.863    | -0.134 | 0.113 |                | 0.593   | -0.091 | 0.158 |                | 0.152   | -0.441 | 0.069 |
|     | Feedback×Global | 0.478    | -0.239 | 0.112 |                | 0.055   | -0.350 | 0.003 |                | 0.167   | -0.108 | 0.619 |
|     | Feedback×Local  | 0.846    | -0.192 | 0.158 |                | 0.553   | -0.230 | 0.123 |                | 0.409   | -0.209 | 0.513 |
| 1+2 | Feedback        | 0.922    | -0.087 | 0.078 |                | 0.000   | -0.268 | -0.108 |                | 0.614   | -0.131 | 0.222 |
|     | Global          | 0.472    | -0.112 | 0.052 |                | 0.577   | -0.103 | 0.057 |                | 0.611   | -0.130 | 0.222 |
|     | Local           | 0.801    | -0.092 | 0.071 |                | 0.696   | -0.095 | 0.064 |                | 0.964   | -0.180 | 0.172 |
|     | Feedback×Global | 0.533    | -0.153 | 0.079 |                | 0.327   | -0.170 | 0.057 |                | 0.568   | -0.177 | 0.322 |
|     | Feedback×Local  | 0.481    | -0.158 | 0.074 |                | 0.937   | -0.117 | 0.108 |                | 0.933   | -0.238 | 0.259 |
**Time-Dependent Trends:** In addition to the primary measure of absolute error that was used in the analysis of the time-dependent trend regarding performance, two additional measures (squared error and square root error) were also used as robustness checks. The results for these robustness checks were directionally consistent with our main finding that providing outcome feedback generally increases performance over time, but can reduce it after cases in which AI “harmed” the participant.

**Figure S8. The robustness checks regarding the time-dependent trends on performance.** Squared error and square root error were used to assess the robustness of our time-dependent trend of performance. The results for squared error and square root error are directionally consistent with our main finding, as providing feedback generally increases performance over time, but can reduce it when AI “harmed” the participant.

**Normalization & Statistical Analysis.** In our prediction task, each participant completed the twelve task instances, of which the first two were for practice purposes and only the last ten were used for data analysis. As such, we conducted tests for differences across conditions at the task level. To prevent the violation of the i.i.d. assumption, all statistical analyses at the task level were based on generalized linear mixed-effects models that included random effects to account for the nested structure of the data. Specifically, we controlled the effects of participant’s characteristics with random coefficients. Additionally, WoA and three performance measures (e.g., absolute error, squared error, square root error) were standardized (z-scored) within each task as per our pre-registration. For example, given a task instance i, a participant’s standardized score on task i can be computed as follows: (participant’s score on task i - mean of all participants’ scores on task i) / (standard deviation of all participants’ scores on task i). These standardizations not only control the effects of varying levels of difficulty among task instances but also enable meaningful comparisons of effect sizes across tasks of different conditions (e.g., interpretability, outcome feedback). Because ROC AUC is calculated at the participant level, statistical analyses for ROC AUC were based on OLS rather than the mixed-effects model. Furthermore, the ROC AUC measure was standardized within each participant. All statistical tests were two-tailed.
Self-report Measure. After completing the experiment, all participants in all conditions were asked about the ease with which they could understand the information provided by the AI system. Specifically, participants were asked, “Having experienced the AI system, was it easy to understand?” and they responded on a 5-point likert scale (where 1 = extremely difficult, 2 = somewhat difficult, 3 = neither easy nor difficult, 4 = somewhat easy, and 5 = extremely easy). Results from this question for each of the two experiments are shown in Figure S9. The average is above 4 (between “somewhat easy” and “extremely easy”) for all conditions in both experiments, except for the outcome feedback + local interpretability condition in the first experiment, where the average is slightly below 4 (between “neither easy nor difficult” and “somewhat easy”). As such, participants did not indicate that they had difficulty understanding the AI system regardless of condition.

Figure S9. The self-reported ease with which participants could understand the information provided by the A.I. system. Participants were asked, “Having experienced the A.I. system, was it easy to understand?” and they responded on a 5-point likert scale (where 1 = extremely difficult, 2 = somewhat difficult, 3 = neither easy nor difficult, 4 = somewhat easy, and 5 = extremely easy). The average scores are shown for each condition in each of the two experiments, with experiment 1 depicted in blue dots and experiment 2 depicted in orange squares. The average scores were between “somewhat easy” and “extremely easy,” for all conditions across both experiments except the feedback + local interpretability condition in experiment 1, for which the average score was between “neither easy nor difficult” and “somewhat easy.”
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