

Explainable Reinforcement Learning Agents Using World Models

Madhuri Singh, Amal Alabdulkarim, Gennie Mansi and Mark O. Riedl

School of Interactive Computing, Georgia Institute of Technology.

{msingh365, amal, gennie.mansi, riedl}@gatech.edu,

Abstract

Explainable AI (XAI) systems have been proposed to help people understand how AI systems produce outputs and behaviors. Explainable Reinforcement Learning (XRL) has an added complexity due to the temporal nature of sequential decision-making. Further, non-AI experts do not necessarily have the ability to alter an agent or its policy. We introduce a technique for using World Models to generate explanations for Model-Based Deep RL agents. World Models predict how the world will change when actions are performed, allowing for the generation of counterfactual trajectories. However, identifying what a user wanted the agent to do is not enough to understand why the agent did something else. We augment Model-Based RL agents with a Reverse World Model, which predicts what the state of the world should have been for the agent to prefer a given counterfactual action. We show that explanations that show users what the world should have been like significantly increase their understanding of the agent’s policy. We hypothesize that our explanations can help users learn how to control the agent’s execution through manipulating the environment.

1 Introduction

Explainable AI (XAI) systems have been proposed to help people understand how AI systems produce outputs and behaviors. Deep Reinforcement Learning (DRL) techniques learn a neural network policy model, which attempts to predict the action that is most likely to lead to future reward. Because sequential, long-term behavior is encoded into the neural policy model, DRL agents are notoriously hard to debug and correct if their execution behavior diverges from user preferences, desires, or expectations.

If an XAI system can help users understand how the agent is responding to the environment, how the policy is making predictions, or how the policy was learned, they may be able to adjust to the agent or the environment, so that the agent’s behavior aligns with our preferences for the policy. Because DRL is applicable to agents and robot planning,

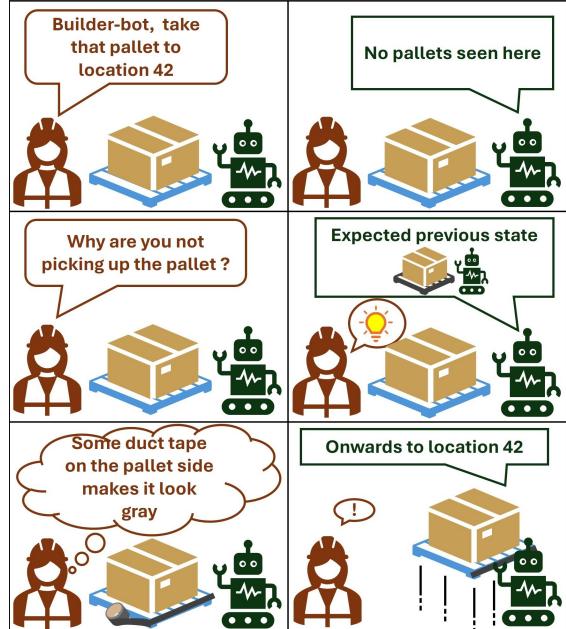


Figure 1: Image depicting how an agent can help a user understand why it is not performing actions to expectations, and how the user might change the world to induce the desired behavior from the agent. In this hypothetical scenario, the user may not have understood the significance of the color of the pallet to the agent. The explanation demonstrates what the environment should have been like for the agent’s policy to execute the desired action. Armed with this new knowledge, the user is able to alter the environment to affect the desired behavior.

many real-world applications, from self-driving cars to personal robotics at home, will have systems driven by DRL interacting with *users without technical background*. Non-AI experts will seek explanations for actions that deviate from their understanding of what the agent should be doing or how it should be doing it [Miller, 2019]. Without an explanation, users can find it difficult to trust the agent’s ability to act safely and reasonably [Zelvelder *et al.*, 2021], especially if they have limited artificial intelligence expertise. Even in the case where the agent is operating optimally and without failure, the agent’s optimal behavior may not match the user’s expectations, resulting in confusion and lack of trust. Non-

AI experts may also wonder what they can do to influence or change the behavior of the agent if they cannot alter the internal workings of the agent or retrain the policy.

Explanation of reinforcement learning systems is especially challenging due to the temporal nature of decision-making—any given decision to perform an action may depend on future expectations as much as, if not more than, current observations. This becomes more complicated when one accounts for users who are not AI experts and, furthermore, do not have the ability to change the algorithm or retrain the agent. What would an *actionable* explanation look like for non-AI experts?

In this paper, we present a technique for using a World Model (WM) to provide actionable information to non-AI experts of DRL systems. A WM describes the agent’s understanding of the state-transition dynamics of the environment. In Model-Based DRL[Kaelbling *et al.*, 1996], the agent learns a World Model through trial-and-error interactions with the environment during training. The World Model is used to predict the effects of the agent’s actions, often speeding up policy learning when interactions with the environment are slow or resource intensive. In the scenario in which the agent fails a task or performs an unexpected action, we show that the World Model can be used to generate a counterfactual explanation that shows the user what the agent would have expected the world state to look like in order to have chosen an action preferred by the user. *The user can then act upon this information to influence the agent’s actions in the future by affecting change on the environment.* This is because the agent’s policy models the relationship between it and the environment with respect to action, and the WM makes that relationship explicit. While the user may not be able to change or re-train the policy, the user can alter the agent’s behavior by directly manipulating the environment if the agent has a robust policy.

World Models used for a reinforcement learning agent to learn its policy only need to predict a probability distribution over states that can follow a given state and a given action, $Pr(s_{t+1}|s_t, a_t)$. We refer to this as the *forward world model*. The forward world model can generate a counterfactual trajectory corresponding to what the user might have indicated that they expected. That is, if we give it an alternative action a_t^\diamond , the WM will tell us what would have happened instead, s_{t+1}^\diamond . What would the environment need to have been like for the agent to pick a_t^\diamond ? Unfortunately, it is not the state the agent was actually in, s_t . We must identify some counterfactual state, s_t^\diamond , that the agent was *not* in at time t that would have induced the agent to prefer a_t^\diamond over a_t . To generate s_{t+1}^\diamond , we require a *reverse world model* that generates $Pr(s_t|s_{t+1}, a_t)$, the distribution over states that we should have been in at time t to pick the action a_t^\diamond that would have delivered us to desired state s_{t+1}^\diamond . See Figure 2.

The predicted counterfactual state s_t^\diamond can be presented to the user as an explanation of what state the world and agent needed to be in for the agent’s policy to have performed the expected/desired action. Using a virtual agent performing household tasks, We show that presentation of these states to non-AI experts improves user understanding of why an agent fails to perform as expected and what would need to change

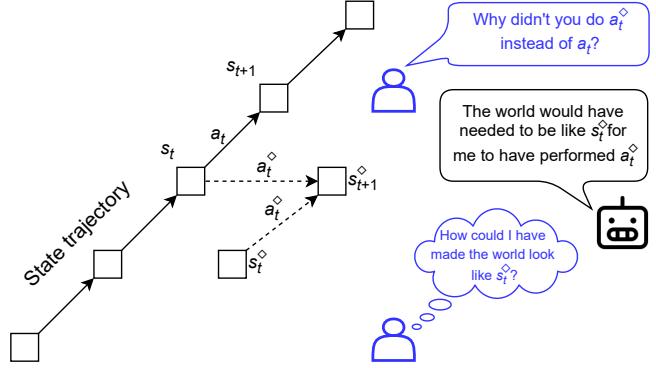


Figure 2: Diagram depicting an agent’s trajectory through state-action space. In state s_t , the agent’s policy preferred action a_t , causing a transition to s_{t+1} . The user wanted the agent to pick action a_t^\diamond . The forward world model can tell us that the effect of a_t^\diamond is state s_{t+1}^\diamond . A reverse world model can generate s_t^\diamond , the state that the agent should have been at time t for its policy to pick the desired a_t^\diamond .

in the environment for the agent to succeed. We further show that our explanations increase user satisfaction, increase user trust, and decrease user cognitive load when trying to identify why the agent failed.

2 Related Work

Explainable Reinforcement Learning (XRL) methods can be classified based on which aspect of the RL agent they explain, which can be at the Policy Level (PL), Feature importance Level (FI), or the learning and Markov Decision Process (LPM) [Milani *et al.*, 2024]. FI methods focus on providing the immediate context for single actions. Directly generated natural language explanation methods, such as rationale-generation [Ehsan *et al.*, 2019], are an example of FI explanations. LPM methods provide additional information on the effects of the MDP or training process, such as influential training experiences or how the agent acts regarding its rewards or objectives. Often, LPM methods require additional information, such as concepts in State2Explanation [Das *et al.*, 2023], graphical causal models [Madumal *et al.*, 2020; Peng *et al.*, 2022], a learned transition model [van der Waa *et al.*, 2018], and partial symbolic model approximations that capture actions and their preconditions [Sreedharan *et al.*, 2022], as well as reward decompositions [Alabdulkarim *et al.*, 2025; Das and Chernova, 2020; Septon *et al.*, 2023]. Lastly, PL explanations summarize long-term behaviors using abstractions or representative examples. Agent Strategy Summarization [Amir *et al.*, 2018] is a representative example of a PL method. Our method is an LPM method that models domain information by learning with the agent’s world model.

Counterfactual explanations, in particular, provide high-level, actionable information which is suitable for non-AI expert users [Gajcic and Dusparic, 2024bl]. People naturally explain in “the form ‘**Why P rather than Q?**’, in which P is the target event and Q is a counterfactual contrast case that did not occur” [Miller, 2019]. Counterfactual (CF) explanations answer the question, what needs to be changed in the input of a computer system such that its output changes to a different

one. In sequential decision-making paradigms the output is the choice of a different action than the one the model has taken or wants to take next. In sequential decision-making, counterfactuals can also take the form of hypothetical future action trajectories to show a user what future expected states could be achieved if an alternative action is taken.

Most closely related to our work are CF explanation systems that generate counterfactual states for which the agent would have chosen a different, desired action if those states were encountered [Olson *et al.*, 2021; Huber *et al.*, 2023; Samadi *et al.*, 2025]. These works employ a second round of training to create a separate, explanation generation model, using action trace data produced by a pre-trained RL agent. This approach has been noted to potentially create counterfactual states that contain the requisite surface features necessary to push the agent to select a new action, but does not guarantee that those states are reachable in the state space [Gajcin and Dusparic, 2024a]. Our technique instead generates explanations from the world model, which is trained as part of the RL agent’s policy training loop. Our technique does not require a separate post-hoc training phase, and the world model—a predictor of successor and predecessor states—is more likely to produce traversable states.

The RACCEr system [Gajcin and Dusparic, 2024a] generates counterfactual states through a search of reachable states for those with the desired properties. It requires access to the execution environment—a simulation, or real-world—to conduct the search. Our technique does not require access to the execution environment, as the world model is a learned surrogate for the environment’s transition dynamics.

COViz [Amitai *et al.*, 2024] takes a different approach to counterfactuals and generates states that are predicted to be visited if an alternative action were to be chosen over the actually chosen action. This is potentially useful information to users in evaluating whether an alternative is better than an actual action choice. This approach is complementary to our work, which helps users determine how to induce the agent to take a different action without explicit override.

3 Generating Actionable Explanations

A critical question in XAI is what an *actionable* explanation would be for reinforcement learning. Actionability refers to how information in explanations helps users take actions in response to an underlying AI system[Mansi and Riedl, 2023]. For an AI system developer, actionable explanations about a RL system often center actions that involve changing the policy, such as correcting the algorithm or altering how the AI system is trained. Non-AI expert end-users cannot change the policy, but explanations for RL systems can still be actionable.

Researchers [Alabdulkarim *et al.*, 2025; Chakraborti *et al.*, 2021; Das *et al.*, 2023] have proposed that explainable RL should update the user’s understanding of how the agent responds to the environment. By changing users’ mental model of the agent, explanations can also help users understand how they can change *their own behavior*. For example, policies are learned responses to the local environmental state respective to task reward. Consequently, explanations can be ac-

tionable by helping users understand how they can change the environment, so the RL system responds as they wish.

In order to enable this kind of actionability, it is critical for users to have a mental model of how changes in the environment influence the agent’s behavior. Our method provides this information by showing users what the environment should have looked like for the agent to take an alternate path. This can allow users to physically alter the environment in order to gain control over an agent, helping users respond to an agent that is not executing as expected or desired.

We hypothesize that non-AI expert end-users should, with our explanations, be able to identify the root cause of what features of local environmental observations resulted in an AI agent performing an unexpected or undesirable action. We test this hypothesis in Section 6. In constructing this understanding, we further speculate that users that receive our explanations can more easily reason about what they could do to adjust the agent’s environment to induce the desired behavior in the future.

4 Preliminaries: Model-Based RL

Before we present our world modeling technique, we review reinforcement learning and the specific version of model-based RL that we build upon.

Reinforcement learning solves sequential decision-making problems. Specifically, it generates a policy, $\pi(s) \rightarrow a$, that maps a state observation s to an action a such that executing the action optimizes future expected reward if the policy is followed henceforth. Deep reinforcement learning approximates the policy with a neural network. The policy model is charged with interpreting the state observation with respect to future expected reward. The policy thus captures the dynamics of the agent with respect to the environment and task.

Model-based reinforcement learning is an RL approach that involves learning an environment model and then using it to train the policy [Kaelbling *et al.*, 1996]. The World Model [Ha and Schmidhuber, 2018], also referred to as the transition dynamics model, approximates the distribution over next state observations given a state and an action: $Pr(s_{t+1}|s, a)$. While a world model is not strictly required for reinforcement learning, in many cases, it reduces the number of interactions an agent must conduct in the actual environment because the agent can simulate world state transitions with its world model.

The DreamerV3 [Hafner *et al.*, 2025] framework is one of the more successful model-based DRL frameworks. It incrementally learns a world model through interactions with the environment and trains the policy against the world model. DreamerV3 comprises of the following models:

$$\text{DreamerV3: } \begin{cases} \text{Sequence model: } h_t = f_\phi(h_{t-1}, z_{t-1}, a_{t-1}) \\ \text{Encoder: } Pr_\phi(z_t|h_t, x_t) \\ \text{Dynamics Predictor: } Pr_\phi(\hat{z}_t|h_t) \\ \text{Decoder: } Pr_\phi(\hat{x}_t|h_t, z_t) \\ \text{Reward predictor: } Pr_\phi(\hat{r}_t|h_t, z_t) \\ \text{Continue predictor: } Pr_\phi(\hat{c}_t|h_t, z_t) \end{cases} \quad (1)$$

where ϕ describes the parameter vector for all distributions optimized, and

- x_t is the current image observation.
- h_t is the encoded history of the agent.
- z_t is an encoding of the current image x_t that incorporates the learned dynamics of the world.
- $s_t = (h_t, z_t)$ is the agent’s compact model state.

Of particular relevance for this work is the dynamics predictor model, $p_\phi(\hat{z}_t|h_t)$, which predicts an image encoding \hat{z}_t given the encoded history of the agent, h_t . For efficiency the DreamerV3 world model operates in the latent embedded state space. Predicted state observations \hat{x}_t can be generated via the image prediction model $Pr_\phi(\hat{x}_t|h_t, z_t)$.

5 Reverse World Models

Model-based RL, and DreamerV3 in particular, learns to predict the (embedded) next state because it is seeking to understand how actions result in *future* expected reward. While the world model is learned primarily to optimize training efficiency with respect to policy performance, we observe that the world model itself can be used to generate counterfactuals—how would the world change if a different action were to be taken. We operate in the setting where the user gives us the counterfactual action, a_t^\diamond , and, by implication, the counterfactual next state s_{t+1}^\diamond . However, the explanation is not what the user already knows or can infer. Our explanation generation strategy hinges on providing the user with an understanding of what the world *should have looked like* prior to s_t for the agent to want to take action a_t^\diamond instead of its actual chosen action a_t . That is, the explanation is constructed around the presentation of s_t^\diamond , the world the agent should have been in to “do the right thing”. A forward world model cannot do this. To generate s_t^\diamond we need a *Reverse World Model*.

The Reverse World Model (RWM) predicts the embedded state $p_\phi(\hat{z}_{t-1}|h_{t-1})$, where h_{t-1} is a function of h_t, z_t and a_{t-1} , and z_t is obtained from x_t . The RWM trains alongside the WM, on a modified copy of the same training data, as follows. First, reward and continuation data is removed. Second, the temporal order of the state-action transition data generated during trials is reversed. DreamerV3 trains its models using an experience replay buffer. DreamerV3 samples chunks of transition data $(x_t, a_t)|_{t=k \dots k+n}$ from the replay buffer. When training the RWM only, we simply reverse the order of the data sampled from the replay buffer. Finally, we shift the actions so that image x_{t+1} and the *prior* action a_t are paired so that when the RWM is trained it predicts the prior embedded state given the future state and prior action.

Once the data processing is done, the RWM proceeds with training based on the usual dynamic and representation losses but with prediction loss only considering the decoder’s image predictions. The DreamerV3 Forward World Model with our combined Reverse World Model is shown in Figure 3. The Reverse World Model produces \hat{z}_t^{rev} , the latent encoding of the prior world state, and \hat{x}_t^{rev} , the reconstructed image from the latent. The RWM module is trained using reconstruction error between the environmental state observation x_t^{rev} and the image decoded from the latent, \hat{x}_t^{rev}

6 Human Participant Study

Since explanations are meant to provide actionable information to non-AI experts, we conduct a human participant study. We hypothesize that non-AI expert end-users should, with our explanations, be able to identify the root cause of what features of local environmental observations resulted in an AI agent performing an unexpected or undesirable action. Specifically, we make the following hypotheses of those who receive explanations relative to those who do not receive an explanation:

- H1. Participants that receive our explanations can more accurately recognize the causes of agent failures.
- H2. Participants that receive our explanations have greater satisfaction in agent responses.
- H3. Participants that receive our explanations have higher trust in the agent.
- H4. Participants that receive our explanations have lower cognitive load when identifying the causes of agent failure.

We ran our human study as an online Qualtrics survey hosted on the Prolific platform. We recruited a total of 70 participants (Control Group strength = 33, Treatment Group strength = 37) in a randomized trial.

The participants were in the age range of 19 to 73 (Mean: 41.3, Standard Deviation: 13.9), with 52.9% people identifying as women and 47.1% identifying as men. The study had a median run time of 21:03 minutes. We paid participants at the rate of \$12.00 per hour, with an added bonus of \$0.50 to be given for high-quality responses, which was given to all participants.

6.1 Study Design

Participants are asked to imagine they are attempting to identify the root cause for why a robot (in a virtual game-like simulation) fails to correctly execute, or inefficiently executes, a task of making coffee. Because we want to control for users’ commonsense understanding, we present a fictional world in which coffee can be made with atypical ingredients like lava, or milk obtained straight from a cow. The recipes also change between the tasks, so the coffee may be made on a stove in one recipe and in a microwave in another.

Participants watch a video of the agent performing its task in a virtual environment built using the Crafter [Hafner, 2022] environment (See Figure 4). Crafter is an extensible 2D implementation of the MineCraft game. We constructed a world consisting of a kitchen and fictional coffee ingredients that can be gathered from nearby environs. The inventory mechanics are maintained, and we implement a new requirement that the agent complete a fictional coffee recipe. Each scenario plays out in a 15×15 grid and the agent can observe a 7×4 window around its position and its inventory.

We present four scenarios, in each of which the agent fails to complete the fictional coffee recipe for a different reason (see description of scenarios below). For each scenario, the participant must identify what was tampered with in the environment that caused the agent to operate ineffectively. In the Control condition, participants were presented with (a) the

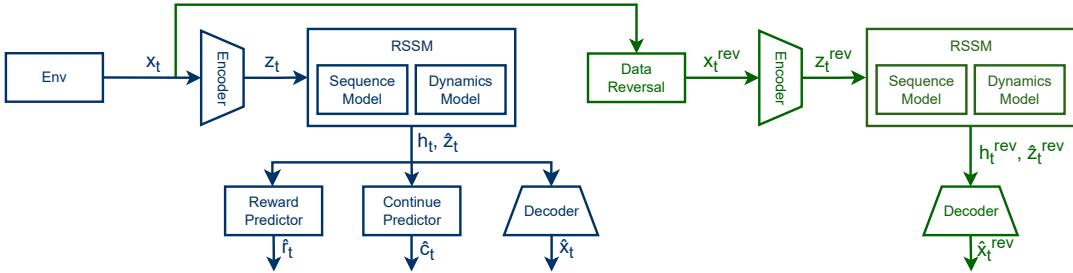


Figure 3: Our modified world model. The left-hand side is the forward world model, as in DreamerV3[Hafner *et al.*, 2025]. The right-hand side shows the reverse world model.



Figure 4: The modified Crafter environment. The agent must interact with various objects to gather ingredients and then interact with various devices to complete the recipe.

video, and (b) four snapshots of states during the agent’s execution. In the Treatment condition, participants were presented with the same information as above, but also (c) each snapshot was paired with a generated image showing what the agent was expecting in order to choose the action that would have resulted in correct execution.

Hypothesis H1 holds if the explanation, in the form of the state expected prior to the counterfactual provides enough information for the participant to pick the reason why the agent chose the wrong action. See Figure 6 in the Appendix.

For the participants to indicate the cause of the failure, they select one of four possible objects from a pre-populated list, and one of four verb-phrases from a pre-populated list. All objects and verb-phrases are probable—each object is present in at least one of the snapshots—but only one combination of object and verb-phrase is correct—there is a 1:16 chance of randomly selecting the correct combination. See Figure 7 in the Appendix.

There was also a free-response text box where participants were asked to describe their reasoning for their choice. This discourages participants from random selection but was not analyzed further.

Scenarios

The four scenarios involved completing the fictional coffee recipe, but under one of the following conditions:

1. A non-essential object is removed
2. An essential object is moved
3. An essential object is obstructed
4. An essential object is removed

The order in which scenarios are presented to participants is randomized.

Surveys

After the four scenarios, participants completed three surveys: satisfaction, trust, and cognitive load.

The satisfaction survey is adapted from Hoffman et al. [Hoffman *et al.*, 2023]. It consists of seven 5-point Likert scale questions that ask about several key attributes of explanation satisfaction. All questions are framed positively, and the answers are supposed to range from ‘Strongly Agree’ to ‘Strongly Disagree’. We mapped these responses as ‘Strongly Agree’=5 down to ‘Strongly Disagree’=1 for simplifying later calculations. We edited the wording of the questions to fit our study while maintaining the same meaning. To have a fair baseline, both the groups were asked these questions about the Error Reports. The error reports presented to the different participant groups differed in that the treatment group received the extra RWM-generated snapshots.

We used the User Trust Survey, also from Hoffman et al. [Hoffman *et al.*, 2023]. This survey consists of eight 5-point Likert scale questions. All questions are framed positively, except one (“I am wary of the tool”).

Our third survey is the NASA Task Load Index (TLX) Survey [Hart and Staveland, 1988], which assesses perceptions of cognitive load. It consists of six questions, each answered on a scale of 21 gradations.

6.2 Agent Configuration

The agent is our modified DreamerV3 model with a reverse world model. It is an Actor-Critic model trained alongside a 25 million parameter FWM and a 25 million parameter RWM. The actor and critic are both MLPs, with learning rates of 3e-5, a batch size of 8 and a batch length of 65. The observation input is an image of a 7x7 grid which depicts the agent’s field of view at a given time step. The full training grid for each static environment is 15x15.

The agent never experiences items being moved, obstructed, or removed during training. It is *intentionally* overfit for purposes of experimental control. While overfit policies

Scenario	% Correct		Odds Ratio	p-value
	Control	Treatment		
Remove Non-Essential Object	3.03	27.03	11.85	0.00571*
Move Essential Object	33.33	86.49	12.80	0.00001*
Obstruct Essential Object	27.27	62.16	4.38	0.00337*
Remove Essential Object	42.42	83.78	7.01	0.00034*
All Scenarios	26.52	64.86	5.12	<0.00001*

Table 1: Fisher’s Exact Test performed per task and cumulatively. Asterisks denote statistical significance.

are generally unwanted, we required an unnaturally brittle agent that would struggle with the task to construct our experimental conditions; it makes the point that no agent in a complex real-world setting can be perfect.

The aim of this human study is to validate whether the RWM generated explanations are genuinely useful to people. To accomplish this, in summary, we trained four RL agents to perform a task in a static environment. We then introduced unexpected changes (e.g. items missing) to said environments and recorded the changed trajectories of the trained agents. We then showed this recording to the study participants along with the RWM-generated expectations of what the agents expected the environment to look like. We then asked these participants if they were able to correctly identify the change.

The agents are the same between experimental and control conditions except for the presentation of the explanations generated by the reverse world model. For each scenario, we selected the point at which the agent deviated from the optimal solution trajectory and three other random points and the snapshots are presented to participants.

7 Results

7.1 Accuracy

We looked at the percentage of participants in each group who got the answers right per scenario. Table 1 shows the average correctness of participant selections. We used Fisher’s Exact Test for categorical data to evaluate statistical significance. Participants in the explanation condition were significantly ($p < 0.008$) more likely to identify the cause of the agent’s problem and correctly assemble that reason using the pre-populated lists of objects and verb phrases. *Hypothesis H1 is supported.*

7.2 Satisfaction

The satisfaction survey results are shown in Figure 5a, which shows the degree of agreement with questions that ask about satisfaction with explanations. We aggregate responses across all questions since they are all directionally the same and look at satisfaction with different aspects of the explanation. Participants in the treatment group were significantly ($p \approx 0.0036$) more likely to agree with statements pertaining to the satisfaction of explanations. This can be seen as a greater mass toward the top of the chart in the treatment group—higher number means more agreement. *Hypothesis H2 is supported.*

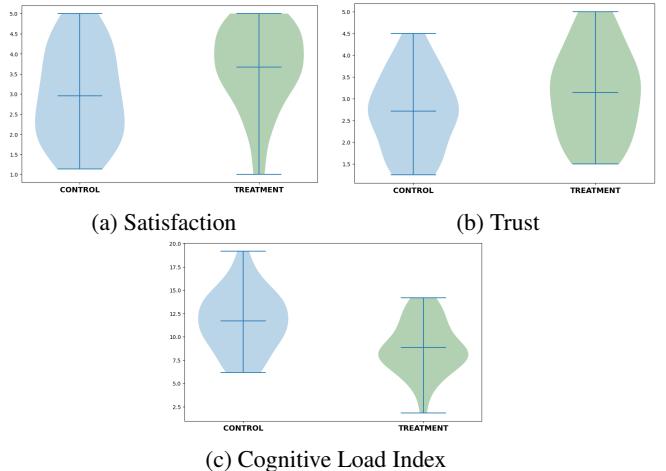


Figure 5: Graphs depicting the distribution of average survey scores assigned by participants for User Satisfaction, Perceived User Trust and Perceived Cognitive Load

7.3 Trust

The satisfaction survey results are shown in Figure 5b. As with the satisfaction results, a higher mass indicates more agreement with statements about trust; for the one question framed negatively, we flipped the axis in order to aggregate the responses with the other questions. Participants in the Treatment group are significantly ($p \approx 0.034$) likely to indicate trust (and less wariness) in the system than those in the Control group. *Hypothesis H3 is supported.*

7.4 Cognitive Load

The cognitive load survey results are shown in Figure 5c. We analyzed the results using the Raw TLX technique [Byers *et al.*, 1989], a simple unweighted mean of all answers to summarize the results per participant. A lower RTXL score indicates lower workload on the participant, which is preferred. Participants in the Treatment group reported significantly ($p \approx 9.76 \times 10^{-5}$) lower cognitive loads. *Hypothesis H4 is supported.*

7.5 Task Completion Time

We recorded the amount of time that participants took to complete each scenario. This encompasses the time they spent reading the status, looking at the video, looking at the images, assembling the response from the pre-populated lists, and writing a short free-text description of how they arrived at the answer. Participants in the Treatment group took on average 3.55 (Std.Dev. 2.57) minutes to complete each scenario. Participants in the Control group took on average 3.68 (Std.Dev. 3.09) minutes to complete each scenario.

A t-test indicates that there is no significant difference in completion times between groups ($p < 0.35$). Table 2 breaks out the time per group and per scenario. Taken along with other results, the explanations in the Treatment Group neither add cognitive load nor add cognitive processing time. Three of four scenarios result in less time, though not significantly so. One scenario took longer on average; this scenario was also significantly harder (per accuracy results in Table 1).

Scenario	Mean Time (Std.Dev)		t-statistic	p-value
	Control	Treatment		
Remove Non-Essential Object	3.80 (2.16)	4.37 (2.23)	1.07	0.86
Move Essential Object	3.75 (2.57)	3.27 (2.93)	-0.72	0.24
Obstruct Essential Object	4.02 (4.78)	3.65 (2.79)	-0.39	0.35
Remove Essential Object	3.16 (1.88)	2.91 (1.97)	-0.53	0.29
All Scenarios	3.68 (3.09)	3.55 (2.57)	-0.38	0.35

Table 2: Table displaying the average time taken (in minutes) by each group to complete tasks.

8 Discussion

We overfit our policy model for experimental purposes because we require an agent that will fail in a relatively simple environment. It is always the case that an RL agent can fail due to real-world complexity, even when trained with robustness in mind. Even if the agent does not fail, the user may find the agent to not be aligned to their preferred way of completing a task. Regardless, the forward and reverse world models must be able to robustly predict state dynamics transitions from parts of the state space that the agent might not commonly visit during training.

The RWM generates predictions of states from within the distribution of what the FWM and agent have trained upon, since FWM and RWM train on the same data. The RWM generated suggestions are hence capable of providing insights into the agent’s expectations that would be difficult to approximate for an explainer that isn’t internal to the agent and wasn’t trained alongside the policy. This, however, also ties the RWM’s capabilities to how well FWM and agent have been trained. To create a more robust RWM that can provide good predictions if the counterfactuals are very different from states that the agent would have routinely explored during training, one might need off-policy exploration strategies such as [Eysenbach *et al.*, 2018; Hafner *et al.*, 2019]. In general, World Models in RL agents are more likely to catastrophically forget state transition dynamics that are not directly relevant to the policy construction [Balloch, 2024].

9 Conclusions

Explainable RL agents for non-AI experts presents a significant challenge because the user cannot change the agent or re-train the policy if it doesn’t perform as expected. To explain why an RL agent chose a particular action over another, counterfactual, action, we generate a state in which the agent would have chosen the user’s desired action. To do this, we extend the RL agent with a reverse world model that can predict and generate counterfactual states that preceded the current state, instead of the more common prediction and generation of future counterfactual states.

Our human participant study demonstrates that generating the prior counterfactual to the desired action can significantly improve users’ abilities to identify the environmental cause of agent failure. It also improves user satisfaction and trust while reducing cognitive load.

The policy encodes the agent’s understanding of how environmental observations map to action that optimizes for fu-

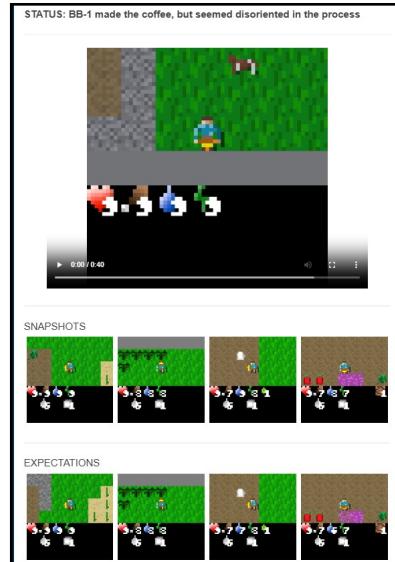


Figure 6: Screenshot of a scenario as presented to participants consisting of an execution video, a list of images depicting the true snapshots and a list of images depicting the RWM’s expectations.

ture task reward. Improving the user’s understanding of the agent’s policy with respect to the environment helps them update their mental model of the agent. This in turn helps them identify the cause of failures or the cause of mis-alignment between user and agent policy. Finally, while not directly studied in the scope of this paper, it also potentially enables the user to correct or align agent behavior through deliberate alterations of the environment.

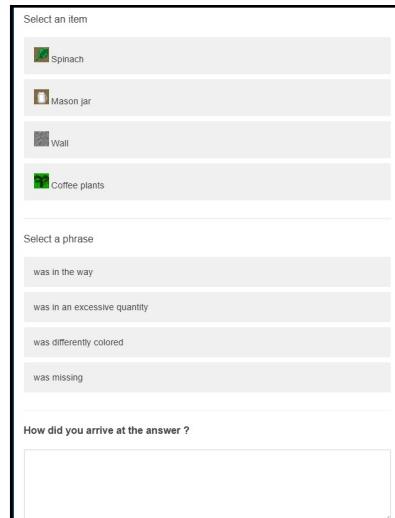


Figure 7: Screenshot of the interface where participants assemble the cause of the agent’s problem from pre-populated lists.

10 Appendix

The core human participant study materials are presented in Figures 6 and 7.

References

- [Alabdulkarim *et al.*, 2025] Amal Alabdulkarim, Madhuri Singh, Gennie Mansi, Kaely Hall, Upol Ehsan, and Mark O Riedl. Experiential explanations for reinforcement learning. *Neural Computing and Applications*, pages 1–31, 2025.
- [Amir *et al.*, 2018] Ofra Amir, Finale Doshi-Velez, and David Sarne. Agent strategy summarization. In *Proceedings of the 17th International Conference on Autonomous Agents and MultiAgent Systems*, pages 1203–1207, 2018.
- [Amitai *et al.*, 2024] Yotam Amitai, Yael Septon, and Ofra Amir. Explaining reinforcement learning agents through counterfactual action outcomes. In *Proceedings of the Thirty-Eighth AAAI Conference on Artificial Intelligence and Thirty-Sixth Conference on Innovative Applications of Artificial Intelligence and Fourteenth Symposium on Educational Advances in Artificial Intelligence, AAAI’24/IAAI’24/EAAI’24*. AAAI Press, 2024.
- [Balloch, 2024] Jonathan Balloch. *Efficient Adaptation of Reinforcement Learning Agents to Sudden Environmental Change*. Doctoral dissertation, Georgia Institute of Technology, 2024.
- [Byers *et al.*, 1989] James C Byers, AC Bittner, and Susan G Hill. Traditional and raw task load index (tlx) correlations: Are paired comparisons necessary. *Advances in industrial ergonomics and safety*, 1:481–485, 1989.
- [Chakraborti *et al.*, 2021] Tathagata Chakraborti, Sarath Sreedharan, and Subbarao Kambhampati. The emerging landscape of explainable automated planning & decision making. In *Proceedings of the Twenty-Ninth International Conference on International Joint Conferences on Artificial Intelligence*, pages 4803–4811, 2021.
- [Das and Chernova, 2020] Devleena Das and Sonia Chernova. Leveraging rationales to improve human task performance. In *Proceedings of the 25th international conference on intelligent user interfaces*, pages 510–518, 2020.
- [Das *et al.*, 2023] Devleena Das, Sonia Chernova, and Been Kim. State2explanation: Concept-based explanations to benefit agent learning and user understanding. *Advances in Neural Information Processing Systems*, 36:67156–67182, 2023.
- [Ehsan *et al.*, 2019] Upol Ehsan, Pradyumna Tambwekar, Larry Chan, Brent Harrison, and Mark O Riedl. Automated rationale generation: a technique for explainable ai and its effects on human perceptions. In *Proceedings of the 24th international conference on intelligent user interfaces*, pages 263–274, 2019.
- [Eysenbach *et al.*, 2018] Benjamin Eysenbach, Abhishek Gupta, Julian Ibarz, and Sergey Levine. Diversity is all you need: Learning skills without a reward function, 2018.
- [Gajcin and Dusparic, 2024a] Jasmina Gajcin and Ivana Dusparic. Racer: Towards reachable and certain counterfactual explanations for reinforcement learning. In *Proceedings of the 23rd International Conference on Autonomous Agents and Multiagent Systems*, AAMAS ’24, page 632–640, Richland, SC, 2024. International Foundation for Autonomous Agents and Multiagent Systems.
- [Gajcin and Dusparic, 2024b] Jasmina Gajcin and Ivana Dusparic. Redefining counterfactual explanations for reinforcement learning: Overview, challenges and opportunities. *ACM Comput. Surv.*, 56(9), April 2024.
- [Ha and Schmidhuber, 2018] David Ha and Jürgen Schmidhuber. World models. 2018.
- [Hafner *et al.*, 2019] Danijar Hafner, Timothy Lillicrap, Ian Fischer, Ruben Villegas, David Ha, Honglak Lee, and James Davidson. Learning latent dynamics for planning from pixels, 2019.
- [Hafner *et al.*, 2025] Danijar Hafner, Jurgis Pasukonis, Jimmy Ba, and Timothy Lillicrap. Mastering diverse control tasks through world models. *Nature*, pages 1–7, 2025.
- [Hafner, 2022] Danijar Hafner. Benchmarking the spectrum of agent capabilities, 2022.
- [Hart and Staveland, 1988] Sandra G Hart and Lowell E Staveland. Development of nasa-tlx (task load index): Results of empirical and theoretical research. In *Advances in psychology*, volume 52, pages 139–183. Elsevier, 1988.
- [Hoffman *et al.*, 2023] Robert R. Hoffman, Shane T. Mueller, Gary Klein, and Jordan Litman. Measures for explainable ai: Explanation goodness, user satisfaction, mental models, curiosity, trust, and human-ai performance. *Frontiers in Computer Science*, Volume 5 - 2023, 2023.
- [Huber *et al.*, 2023] Tobias Huber, Maximilian Demmler, Silvan Mertes, Matthew L. Olson, and Elisabeth André. Ganterfactual-rl: Understanding reinforcement learning agents’ strategies through visual counterfactual explanations. In *Proceedings of the 2023 International Conference on Autonomous Agents and Multiagent Systems*, AAMAS ’23, page 1097–1106, Richland, SC, 2023. International Foundation for Autonomous Agents and Multiagent Systems.
- [Kaelbling *et al.*, 1996] Leslie Pack Kaelbling, Michael L Littman, and Andrew W Moore. Reinforcement learning: A survey. *Journal of artificial intelligence research*, 4:237–285, 1996.
- [Madumal *et al.*, 2020] Prashan Madumal, Tim Miller, Liz Sonenberg, and Frank Vetere. Explainable reinforcement learning through a causal lens. In *Proceedings of the AAAI conference on artificial intelligence*, volume 34, pages 2493–2500, 2020.
- [Mansi and Riedl, 2023] Gennie Mansi and Mark Riedl. Why don’t you do something about it? outlining connections between ai explanations and user actions, 2023.
- [Milani *et al.*, 2024] Stephanie Milani, Nicholay Topin, Manuela Veloso, and Fei Fang. Explainable reinforcement learning: A survey and comparative review. *ACM Computing Surveys*, 56(7):1–36, April 2024.

- [Miller, 2019] Tim Miller. Explanation in artificial intelligence: Insights from the social sciences. *Artificial intelligence*, 267:1–38, 2019.
- [Olson *et al.*, 2021] Matthew L. Olson, Roli Khanna, Lawrence Neal, Fuxin Li, and Weng-Keen Wong. Counterfactual state explanations for reinforcement learning agents via generative deep learning. *Artificial Intelligence*, 295:103455, 2021.
- [Peng *et al.*, 2022] Xiangyu Peng, Mark Riedl, and Prithviraj Ammanabrolu. Inherently explainable reinforcement learning in natural language. *Advances in Neural Information Processing Systems*, 35:16178–16190, 2022.
- [Samadi *et al.*, 2025] Amir Samadi, Konstantinos Koufos, Kurt Debattista, and Mehrdad Dianati. Counterfactual explainer for deep reinforcement learning models using policy distillation. *ACM Trans. Intell. Syst. Technol.*, 16(2), February 2025.
- [Septon *et al.*, 2023] Yael Septon, Tobias Huber, Elisabeth André, and Ofra Amir. Integrating policy summaries with reward decomposition for explaining reinforcement learning agents. In *International Conference on Practical Applications of Agents and Multi-Agent Systems*, pages 320–332. Springer, 2023.
- [Sreedharan *et al.*, 2022] Sarath Sreedharan, Utkarsh Soni, Mudit Verma, Siddharth Srivastava, and Subbarao Kambhampati. Bridging the gap: Providing post-hoc symbolic explanations for sequential decision-making problems with inscrutable representations. In *International Conference on Learning Representations*, 2022.
- [van der Waa *et al.*, 2018] J van der Waa, J van Diggelen, K van den Bosch, and M Neerincx. Contrastive explanations for reinforcement learning in terms of expected consequences. *XAI 2018*, page 165, 2018.
- [Zelvelder *et al.*, 2021] Amber E Zelvelder, Marcus Westberg, and Kary Främling. Assessing explainability in reinforcement learning. In *International Workshop on Explainable, Transparent Autonomous Agents and Multi-Agent Systems*, pages 223–240. Springer, 2021.