RESPONSE

Thanks to all the reviewers for their constructive feedback. We give more detailed responses here.

1. Detailed Explanations for Figures

We apologize for the unclear description of the figures. In this section, we provide a detailed illustration of each figure. Meanwhile, adequate explanations will be added to the revision.

Figure 1: Figure 1 illustrates some examples of the limitations of task-related data: (a) Image salient object detection: People with different knowledge backgrounds perceive salient targets in the same image differently, e.g. architects perceive the house as the salient object while gardeners perceive plants as salient objects. (b) Vehicle trajectory anomaly detection: The reason why the driver's actual trajectory (red) is very different from the expected trajectory (blue) is that the driver forgot to go to the shop, so the red trajectory is normal. Therefore, in realistic tasks, relying only on task-related data cannot yield reasonable decisions.

Figure 2: This figure shows the overall framework of our proposed cognitive model. The bottom-up phase includes the knowledge learning of POMDP model and the value assignment of influencing factors. The top-down phase provides a generic interpretable structure based on knowledge flow.

Figure 3: In this figure, $S_{t+1}, O_{t+1}, A_{t+1}$ denote the state, observation and action space at time $t+1$. For the policy π_{re} of task-related data, every action is independent of the current state that is given from the history trajectory. In the policy π_{ag} of task-agnostic data, however, the action is no longer independent of the current state.

Figure 4: An example of the trapezoidal schema for knowledge flow is given in Figure 4. In this process, we consider the same class of data as a factor, for example, whether the trajectories of two vehicles overlap in vehicle anomaly following detection is treated as the "trajectory" factor. Figure 4 gives five factors as examples. Through bottom-up knowledge learning, the five factors are ranked according to their value to the decision. θ is a trigger parameter for knowledge flow. When the value difference between two factors exceeds θ, the factor with smaller value will flow to the next layer.

Figure 5: Figure 5 is an overall depiction of abnormal vehicle following detection. The factors considered in this task are trajectory, social factors, and driver factors. For different tasks and special realistic cases, the selection and consideration of influencing factors may be different. In this paper, we select the general case for experiments. Although the influencing factors applied to the various tasks are different, the data processing ability, comprehensive decision-making ability, and knowledge expression ability of our proposed framework are not affected.

Figure 6: We give the decision-making results of the proposed framework under varying task-agnostic factors. Specifically, the transfer probability of a task-agnostic factor is changed, while the other factors are kept constant in the experiment. As can be seen from the figure, our framework can respond accordingly to changes in different factors. And this response is in accordance with human cognition. For example, as the crime rate in the city increases, the probability of the same following behavior being identified as "Abnormal" will also increase.

Table 1: Comparison with Task-related Models

Algorithms	Parameters	Related Data	Agnostic Data	Accuracy	NMI
k-means	k=350	√	×	0.8475	0.9814
k-medoids	k=350	√	×	0.8750	0.9848
DBSCAN	epsilon=0.5; MinPts=1;	√	×	0.8635	0.9826
Ours	–	√	√	0.9625	0.9953

Figure 7: Figure 7 specifically describes the impact of changes in the *CR* factor in Figure 6 on the final decision. In the experiment, we mainly prove that our model has the ability, i.e., knowledge learning and knowledge representation, to handle complex real-world tasks. Here, we believe that the current AI models still cannot completely replace human experts for decision-making, but more to help human decision-making. For example, in a city with a high crime rate, even if the agent gives a 60% probability that the event is abnormal, the police will not necessarily deal with it because there are too many crimes in the city. However, the police in some civilized cities may investigate events even when the agent gives a 40% anomalous probability because civilized cities have a low tolerance for criminal behaviors. Therefore, we make more efforts to verify the data processing ability, comprehensive decision-making ability, and knowledge expression ability of our model in the experiment, without special emphasis on the result accuracy.

Figure 8: This figure uses the JS-devergence curve to verify the convergence speed of the POMDP model with (red) and without (blue) task-agnostic data intervention. From the results, it can be seen that the convergence rate of the model incorporating task-agnostic data is significantly better than that of the model using only task-related data.

Figure 9: The k-means algorithm is compared with our cognitive framework. Regarding the experimental data, we synthesize 200 pairs of trajectories representing 200 following events. The 100 pairs are completely dissimilar, which means that there must be no abnormal following behavior in these 100 events. The other 100 pairs are overlapping trajectories, of which 50 pairs are abnormal following trajectories and the other 50 pairs are normal following trajectories. Here, the reason why the trajectories overlap but are recognized as normal following is the intervention of task-agnostic data. For the comparison model, we only used the k-means algorithm here. We try to deploy some of the state-of-the-art methods that can make use of task-related and task-agnostic data for decision making, but the results are not satisfactory.

Figure 10: We compare the proposed framework with human decision making. The values of all factors are normalized to between 0.1 and 0.9 for a fair comparison. At the same time, we can also clearly see that our cognitive framework is capable of expressing knowledge in addition to making decisions, which is essential for the agent to handle complex real-world tasks.

2. Comparison with Task-related Models

We extend the experiments in the manuscript Section 5.4. The k-means algorithm, the k-medoids algorithm and the DBSCAN algorithm are compared with our cognitive framework. The experimental setup and dataset are consistent with those described in the manuscript. The comparison results are shown in Table 1.