We thank the reviewers for their insightful feedback. We are encouraged that they find the proposed algorithm for generating value of information (VoI)-based macro-actions in POMDPs novel (*R1*, *R3*, *R4*), intuitive (*R3*, *R4*), and the theoretical analysis carefully written and explained (*R1*). Reviewers highlighted the generalizability to many domains (*R2*), including multiagent planning (*R1*), and the benefit to the community of the theoretical regret bound (*R1*, *R2*, *R4*). We address reviewer comments below and begin by situating the paper's intended contribution:

- **What is our goal?** We introduce a metric (value of information (VoI)) for quantifying when the information provided by sensing is most useful in partially observable planning problems. We utilize this metric to develop an algorithm with accompanying theoretical performance guarantees for generating and effectively using open-loop macro-actions in partially observable planning problems without sacrificing policy performance.

- **Why is this our goal?** VoI is highly variable within many planning problems – task performance relies crucially on information-gathering from some belief states, and significantly less so from others. We show how to exploit this property to reduce planning complexity in a way that current POMDP algorithms do not. With VoI macro-actions, POMDP planners incur the complexity of full, closed-loop planning only when necessary. Counter to (*R2*), that low VoI is "contrary to the core concept of POMDPs", VoI macro-actions expand the set of problems that can be efficiently solved using POMDP methods, but are guaranteed to recover the performance of closed-loop POMDP planners in classical domains such as Tiger that exhibit uniformly high VoI.

- **What is not our goal?** The primary critique of reviewers is the limited scope of our experimental results. (*R1*, *R2*, *R3*) suggest validation on standard POMDP benchmark problems. While benchmark problems are certainly important, the dynamic tracking problem allows us to directly vary the value of information and evaluate algorithm performance. The goal of these experiments is not to outperform state-of-the-art baselines on standard POMDP tasks, but to demonstrate that there is a class of problem for which reducing the size of the reachable belief space using VoI macro-actions can be achieved without sacrificing policy performance.

  We agree that further empirical validation of our work is an important next step. However, given limited space, we chose to focus on providing a clear and extensive treatment of our algorithm and theoretical results, which reviewers highlight (*R1*, *R2*, *R4*). The reviewers state that they are "sure of the idea and its potential impact" (*R4*) and that it represents a "novel, interesting, and principled contribution" (*R1*), despite the limited experiments. All reviewers agree on the novelty and impact of the algorithm and analysis, which we believe to be a significant contribution.

1. Experimental Scope - Dynamic Tracking Experiments (*R1*, *R2*, *R3*, *R4*) Unlike fixed POMDP benchmarks, the dynamic tracking experiments allow us to evaluate planner performance across a spectrum of VoI (conditions (i)-(iii) suggested in the text). The goal of these experiments is to validate the performance guarantees presented in Theorem 5.2 — not to compete with state-of-the-art POMDP algorithms on benchmark problems (many of which are designed to test planner performance under uniformly high VOI conditions). We agree that exploring the VoI structure in a few of the benchmark POMDP problems mentioned by reviewers (*R1*, *R2*, *R3*) is an interesting avenue for future work.

(*R3*) points to the marginal improvement over closed-loop in our random walk domain — however, random walk was included precisely to demonstrate our theoretical claim that VoI macro-action polices recover the performance of closed-loop POMDP algorithms in high VoI problems like the random-walk experiment. We will clarify this in the text.

(*R4*) was curious about experimental results under different VoI regimes – we are also excited about these results and will include an ablation study in the camera-ready under the low VoI conditions introduced in the text.

2. Experimental Scope - State-of-the-art Algorithms (*R1*, *R2*, *R3*) Reviewers request a comparison to state-of-the-art POMDP baselines, such as SARSOP. We emphasize that our algorithm and theoretical results hold for any approximation of the closed-loop value function, including that produced by SARSOP. Currently, we use PBVI as the base closed-loop algorithm for macro-action construction - therefore, comparing to PBVI directly demonstrates of the benefit of open macro-actions. We will modify the potentially misleading terminology "best closed-loop".

(*R1*, *R2*) thoughtfully suggest using SARSOP as the base algorithm for generating macro-actions. This is an interesting idea — SARSOP is designed to more effectively *search* a policy's reachable belief space; VoI macro-actions actually *shrink* this reachable belief space. Combining these complimentary strategies is an exciting area of future work.

3. Multiple-hypothesis testing (*R1*) We have updated the significance test to control the false positive rate of both comparisons using the Bonferroni correction — the experimental claims and significance comparison remain the same.

4. Hyperparameters (*R1*) Hyperparameter settings were dictated by computational constraints in this larger experimental domain. All algorithms are run with the same hyperparameters to evaluate the impact of VoI macro-actions.

5. Definition of terms (*R3*) Definitions of common terms, such as open- and closed-loop, are omitted due to space limitations. For definition of optimally reachable belief space (RBS*) and VoI, see Ln. 19 and Eq. (4) respectively. We agree that the figure captions should be more self-contained, and will add a definition for RBS* in the caption of Fig. 1.