

KGLAMP: Knowledge Graph-guided Language model for Adaptive Multi-robot Planning and Replanning

Chak Lam Shek^{1,2} Faizan M. Tariq¹ Sangjae Bae¹ David Isele¹ Piyush Gupta¹

Abstract—Heterogeneous multi-robot systems are increasingly deployed in long-horizon missions that require coordination among robots with diverse capabilities. However, existing planning approaches struggle to construct accurate symbolic representations and to maintain plan consistency in dynamic environments. Classical PDDL planners require manually crafted symbolic models, while LLM-based planners often ignore agent heterogeneity and environmental uncertainty. We introduce *KGLAMP*, a knowledge-graph-guided LLM planning framework for heterogeneous multi-robot teams. The framework maintains a structured knowledge graph encoding object relations, spatial reachability, and robot capabilities, which guides the LLM in generating accurate PDDL problem specifications. The knowledge graph serves as a persistent, dynamically updated memory that incorporates new observations and triggers replanning upon detecting inconsistencies, enabling symbolic plans to adapt to evolving world states. Experiments on the MAT-THOR benchmark show that *KGLAMP* improves performance by at least 25.5% over both LLM-only and PDDL-based variants.

I. INTRODUCTION

Heterogeneous multi-robot systems are increasingly deployed in real-world missions, including disaster response, warehouse logistics, and large-scale inspection [1]. By integrating robots with diverse capabilities and embodiments, these systems can effectively accomplish complex missions that are beyond the reach of homogeneous teams. The heterogeneity among robots introduces substantial challenges in long-horizon planning tasks, including task allocation and the coordination of robot actions in dynamic and uncertain environments [2]. To this end, recent work has focused on planning strategies for effectively integrating heterogeneous robots with diverse roles and capabilities.

Despite recent progress, effective planning for heterogeneous teams remains challenging [3], [4]. Planning Domain Definition Language (PDDL)-based approaches offer strong guarantees for long-horizon planning but depend on manually crafted domain and problem specifications [5]. These specifications are labor-intensive to construct, and even minor modeling errors can induce brittle behavior, as planners assume complete and consistent environmental representations.

Recent advances in large language models (LLMs) reduce the manual burden of domain specification [6] and enable

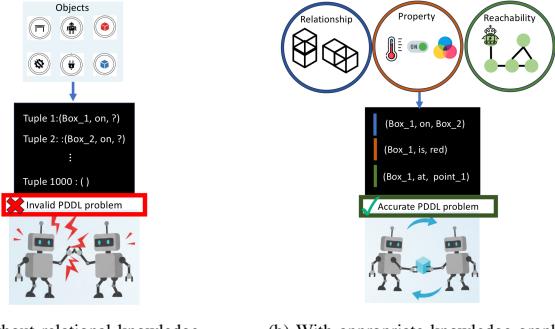


Fig. 1: Impact of relational knowledge on task planning. (a) Without relational graphs, PDDL models fail to capture object relationships, leading to infeasible actions. (b) Integrating relationship, property, and reachability graphs enables accurate PDDL generation and feasible task plans.

flexible high-level reasoning for long-horizon planning [7]. Prior work shows that LLMs can generate PDDL specifications and support symbolic planners [8], [9]. However, LLM-based planning remains challenging for heterogeneous multi-robot systems [10], as most methods assume shared action models and identical capabilities, limiting reasoning over embodiment, skills, and feasible task assignments [11]. As illustrated in Fig. 1, without relevant relational context, generated plans often fail to capture inter-robot dependencies, coordinated timing, and shared resource constraints critical for effective cooperation in heterogeneous teams.

Another limitation is the common assumption of complete and accurate environment information. In real-world settings, object states, spatial layouts, and task-relevant properties cannot always be consistently maintained [12], leading to mismatches between symbolic planner representations and the true operational context. Effective multi-robot systems must therefore monitor their knowledge, update internal representations, and adapt plans as new information becomes available. Addressing these issues is critical for reliable long-horizon planning in heterogeneous multi-robot teams.

To address these challenges, we introduce *KGLAMP*, a knowledge-graph-guided LLM planning framework for heterogeneous multi-robot systems. *KGLAMP* encodes environment structure and robot capabilities as interconnected knowledge graphs capturing object relations, spatial connectivity, and agent-specific properties (Fig. 1b). Grounded in these structured representations, the LLM generates planning domain and problem descriptions that yield symbolic tasks better aligned with real-world conditions.

¹Honda Research Institute, USA, San Jose, CA, 95134.

²University of Maryland, College Park, MD 20742, USA.

All work was performed during the internship of Chak Lam Shek while he was employed at HRI. Corresponding authors: cshek1@umd.edu, piyush.gupta@honda-ri.com.

This work has been submitted to the IEEE for possible publication. Copyright may be transferred without notice, after which this version may no longer be accessible.

The knowledge graph further serves as a persistent memory that tracks the environment state by integrating new observations, updating inconsistent information, and propagating changes across related entities. This enables the planner to adapt to changing world knowledge and efficiently replan when discrepancies arise, supporting the robust operation of heterogeneous robot teams in dynamic environments.

The main contributions of this work are:

- 1) A unified *knowledge-graph representation that grounds LLM-based planning* by modeling object relations, spatial reachability, and semantic properties.
- 2) An incremental knowledge-graph update mechanism that integrates new observations, maintains consistency, and supports *replanning in dynamic environments* during failures.
- 3) An empirical evaluation on heterogeneous multi-robot tasks demonstrating improved robustness and coordination over LLM-only and PDDL-based baselines.

II. RELATED WORK

Recent work has extended long-horizon planning to more realistic real-world settings [13]. However, traditional symbolic planners such as PDDL struggle to generalize under real-world complexity and uncertainty, motivating LLM-based approaches for long-horizon planning [14].

Structured planning representations improve interpretability and robustness in complex tasks. Hierarchical abstractions, including Planning with Hierarchical Trees [15] and Behavior Trees [16], enable scalable robotic behavior via modular decomposition. In open-world domains, structured skill graphs (e.g., Plan4MC [17]) and iterative planning frameworks such as PLAN-AND-ACT [18] further improve long-horizon reliability.

This line of work has naturally extended to multi-agent settings [2], where coordination and dependency management are central challenges. SMART-LLM introduces structured, LLM-guided role assignment and coordination [19], while graph-enhanced LLMs explicitly model dependencies to improve asynchronous multi-agent reasoning [20], [21].

More recently, research has moved beyond homogeneous teams to heterogeneous systems with diverse capabilities. This shift introduces challenges in competency-aware task allocation, cross-skill coordination, and dynamic role adaptation. Corresponding advances address these challenges via compositional coordination strategies [22], LLM-guided heterogeneous collaboration [23], LLM-driven PDDL planners [11] for multi-agent task allocation.

Despite promising benchmark results, many existing approaches struggle to generalize to real-world settings due to inconsistent reasoning and the absence of persistent, task-relevant state. These issues are amplified in heterogeneous multi-robot systems, where differing capabilities require a consistent shared understanding for effective coordination. While prior work explores memory mechanisms for long-horizon reasoning—including multi-memory architectures [24], retrieval-augmented planning [25], spatio-temporal navigation memory [26], hybrid multimodal mem-

```
(:predicates (at ?r ?1) (connected ?l1 ?l2))
(:action move
  :parameters (?r ?from ?to)
  :precondition (and (at ?r ?from) (connected ?from ?to))
  :effect (and (not (at ?r ?from)) (at ?r ?to)))
```

(a) Domain PDDL (STRIPS action schema)

```
(:objects robot1 room1 room2)
(:init (at robot1 room1) (connected room1 room2))
(:goal (and (at robot1 room2)))
```

(b) Problem PDDL (task instance)

Fig. 2: Minimal STRIPS PDDL example illustrating (a) Domain PDDL and (b) Problem PDDL

ory [27], long and short term memory systems [28], and lifelong planning memory [29]—most lack structured representations for tracking evolving goals, heterogeneous agent states, and environmental changes across planning iterations. Motivated by these limitations, we introduce a memory-management framework for heterogeneous multi-agent planning that enables persistent, structured state retention and improves coordination among robots.

III. PROBLEM FORMULATION AND PRELIMINARIES

We study long-horizon planning in heterogeneous multi-robot systems, where robots have diverse skills and constraints. For example, in a household setting, heterogeneous robots collaborate to prepare food from high-level natural language instructions that omit explicit actions, preconditions, and ordering constraints. Executing such requests requires inferring task structure, decomposing it into sub-tasks, reasoning about dependencies, and allocating responsibilities across robots that can act in parallel when possible.

A. Multi-Agent Planning (MAP) Formulation

We formulate the problem using a cooperative Multi-Agent Planning (MAP) framework. A MAP instance is defined by the tuple $\langle \mathbb{R}, \mathbb{D}, \{\mathbb{A}_i\}_{i=1}^n, \mathbb{P}, I, G \rangle$, where $\mathbb{R} = \{r_1, \dots, r_n\}$ denotes the set of robots. Each robot r_i is associated with a domain $d_i \in \mathbb{D}$ that captures its capabilities and constraints, and an action set \mathbb{A}_i that describes the state transitions. The state of the environment is modeled as a collection of logical predicates \mathbb{P} , with the initial state $I \subseteq \mathbb{P}$ and goal conditions $G \subseteq \mathbb{P}$.

A plan is denoted as $\Pi = (\Delta, \prec)$, where Δ is a set of instantiated robot actions and \prec is a partial order encoding causal and temporal constraints. The plan is valid if its execution from I reaches a state satisfying G .

B. Planning Domain Definition Language (PDDL)

In PDDL, a planning task is defined by a domain file (Fig. 2a) and a problem file (Fig. 2b). The domain specifies reusable symbolic knowledge, including predicate symbols and parameterized action schemas whose preconditions and effects induce deterministic state transitions over ground atoms. We focus on classical STRIPS-style planning [30], where preconditions are conjunctions of positive literals and effects are add–delete lists.

The problem file instantiates a specific task by declaring a finite set of objects, an initial state I under the closed-world assumption, and a goal condition G as a conjunction

of ground literals. A planner then computes a sequence of grounded actions whose execution from I satisfies G .

IV. METHODOLOGY

In real-world cluttered scenes, even with access to object inventories, LLM-based PDDL generation from long, unstructured memory is error-prone, often resulting in missing constraints, hallucinated predicates, or semantically invalid PDDL. Grounding the LLM with a structured knowledge graph organizes relevant entities and relations, reducing context overload and improving the reliability of PDDL generation. To this end, we introduce *KGLAMP*, a knowledge-graph-guided LLM-based long-horizon planning framework for heterogeneous multi-robot teams. KGLAMP consists of two key components: (1) knowledge graphs that ground the LLM in structured representations of the environment and robot capabilities, and (2) a replanning module that updates plans online when execution deviates from expectations.

The framework translates high-level natural language instructions into executable robot plans via a sequence of specialized LLM agents. As shown in Fig. 3, the pipeline encodes user instructions in prompts and visual scene observations into structured symbolic representations using knowledge graphs. Subsequently, LLM_{goal} , $LLM_{relation}$, $LLM_{property}$, and LLM_{reach} extract goal specifications, spatial hierarchies, object states, and navigational constraints, respectively. These outputs are integrated to construct a complete PDDL problem, which is solved by a PDDL planner (e.g., Fast Downward [31]) to generate an action sequence. The plan is executed sequentially with failure monitoring. Upon failure detection, the system triggers the replanning procedure in Alg. 1, which uses a Vision-Language Model (VLM) to update the knowledge graphs and synthesize a corrected plan. We provide more details about replanning in Section IV-C.

A. Knowledge Graph

A knowledge graph provides a structured abstraction of world information by encoding entities and their semantic relations. Formally, a knowledge graph $\mathcal{G} = (\mathcal{V}, \mathcal{R}, \mathcal{E})$ consists of entities \mathcal{V} , relation types \mathcal{R} , and directed edges $\mathcal{E} \subseteq \mathcal{V} \times \mathcal{R} \times \mathcal{V}$ represented as triplets. Each triplet is of the form (subject, relation, object) or (entity, relation, property), capturing both inter-entity relations and attribute-level information in a unified representation. This structure supports efficient querying and provides a stable semantic foundation for symbolic reasoning.

In *KGLAMP*, the knowledge graph (Fig. 4) is constructed as the union of three components,

$$\mathcal{G} = \mathcal{G}_{relation} \cup \mathcal{G}_{property} \cup \mathcal{G}_{reach}, \quad (1)$$

each encoding a distinct class of relational knowledge required for planning. This structured decomposition mitigates the difficulty of extracting heterogeneous predicates from a single undifferentiated graph: task descriptions may omit semantic relations, physical attributes, or spatial constraints, and LLMs struggle to infer all categories jointly. By partitioning the graph, predicate extraction is decomposed into

smaller, tractable subproblems, enabling systematic grounding of object relations, agent capabilities, and navigability. Specifically, the Relationship graph, $\mathcal{G}_{relation}$, captures semantic and geometric object relationships that inform action preconditions and task structure (e.g., (cup, on, table)); the Property graph, $\mathcal{G}_{property}$, encodes object attributes and robot capabilities, constraining feasible actions and ensuring that planning respects physical and functional limitations (e.g., (robot_A, has_capability, pickup)); and the Reachability graph, \mathcal{G}_{reach} , links entities to discrete locations, enabling navigability reasoning by grounding goals to reachable target locations (e.g., (microwave, at_location, location_1)).

Together, these graphs ground the LLM with semantic, capability, and spatial information, enabling structured task decomposition and accurate PDDL generation aligned with the environment and robot capabilities.

B. PDDL Generation Using knowledge graphs

Generating a correct PDDL problem is inherently challenging, as minor inconsistencies in object labels, relations, or properties can invalidate the entire specification for symbolic planners. This difficulty is amplified in multi-robot domains, where tasks are often ambiguous and involve complex interactions. To address this, we employ a structured pipeline in which multiple LLMs incrementally construct the PDDL problem, grounded in the knowledge graph.

1) *Goal Extraction*: The process begins by translating a natural-language *Task* description into a formal goal specification. Human instructions are often ambiguous, under-specified, or misaligned with the environment state, requiring contextual grounding to produce a valid PDDL goal. Conditioning LLM_{goal} on the environment *Objects* (see example prompt in Fig. 5) yields a goal representation consistent with the instantiated entities, attributes, and relations:

$$Goal = LLM_{goal}(Task, Objects). \quad (2)$$

2) *Relationship-Graph Relations*: Once the goal is extracted, $LLM_{relation}$ infers the object-object relations required for planning. These relations encode the structural organization of entities and directly constrain action applicability and ordering. For example, spatial and containment relations determine action feasibility (e.g., reachability or obstruction) and the preconditions that must hold prior to execution. Identifying these relations before action generation is therefore critical, as they define the structural constraints governing valid action sequences. This inference is grounded in $\mathcal{G}_{relation}$, yielding:

$$Relation = LLM_{relation}(Goal, Task, \mathcal{G}_{relation}). \quad (3)$$

3) *Property Assignment*: With the relational structure established, $LLM_{property}$ assigns object attributes and robot capabilities that further constrain feasible actions. These properties determine whether an entity can participate in an action and if a robot has the required skills or affordances to achieve the goal. Accurate property assignment is therefore critical for pruning infeasible actions and ensuring goal

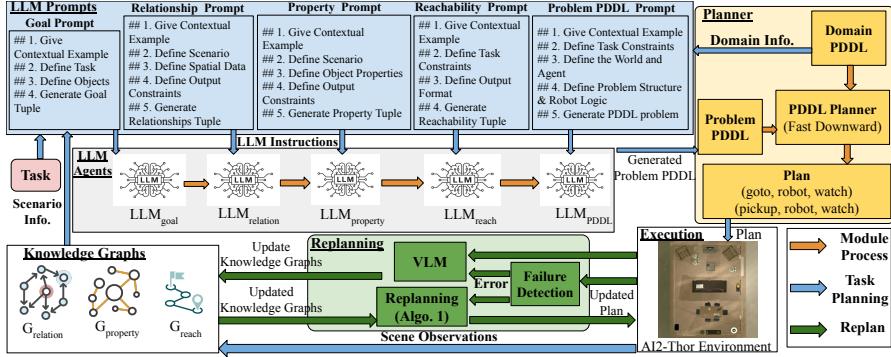


Fig. 3: Overview of KGLAMP framework. Environment and robot information are encoded as relationship, property, and reachability knowledge graphs. LLM agents generate goal, relational, property, and reachability predicates in a dependency-aware manner to synthesize a PDDL problem, execute the resulting plan, and iteratively update the graphs and replan upon execution failures.

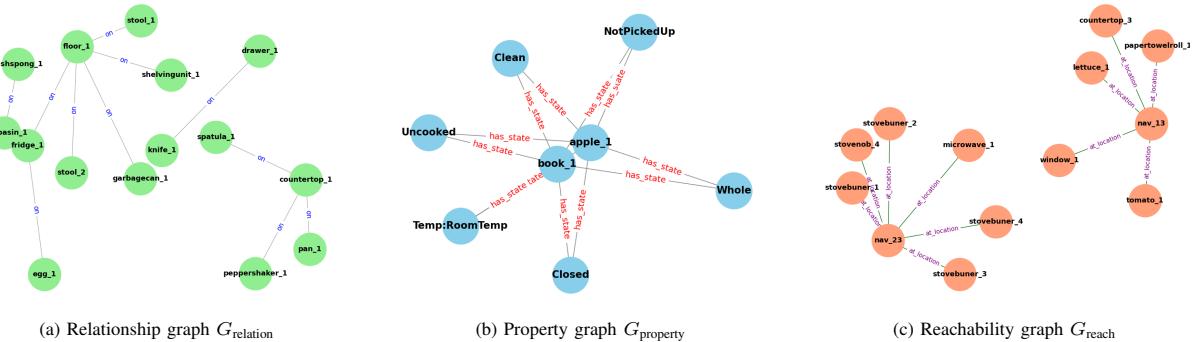


Fig. 4: An example knowledge graph. (a) G_{relation} captures semantic and geometric relationships among objects. (b) G_{property} encodes object attributes and robot capabilities. (c) G_{reach} models spatial connectivity.

```
# Relationship Agent Prompt Structure
This flow demonstrates how the
`generate_relationship_condition` function constructs the
prompt to define the scene's physical hierarchy (containers and
surfaces).

## 1. Give Contextual Example
> * **Content:** Definitions for `(inside ?obj ?container)` .
> * **Support:** Definitions for `(on ?obj ?surface)` .

## 2. Define the Scenario
> "Goal: {goal}"
> Task: {task}"

## 3. Define the Spatial Data
> "Scene Tuples: {scene_tuples}"
> *Raw list of spatial relationships detected in the scene.*"

## 4. Define the Output Constraints
> "Generate relationship condition as PDDL `(:init)` format,
- 1. **Relations:** Only show content relative to `?contain` (inside or on` (supported by).
- 2. **Relevance:** Only include objects that are related to
the `?Goal` or `?Task` (ignore irrelevant background clutter)."
```

Fig. 5: An example of LLM prompt for LLM_{relation} . This prompt utilizes contextual examples, scenario definition, spatial data, and output constraints to extract relevant spatial tuples.

achievability given the available robots and objects. Missing or incorrect attributes and capabilities can cause the planner to propose invalid actions or fail to reach the desired goal state. This inference step leverages $\mathcal{G}_{\text{property}}$, yielding:

$$\text{Property} = \text{LLM}_{\text{property}}(\text{Goal}, \text{Task}, \text{Relation}, \mathcal{G}_{\text{property}}). \quad (4)$$

4) Navigation Structure: We explicitly decouple navigation reasoning from object interaction, as jointly reasoning over spatial motion and manipulation constraints substantially increases multi-robot planning complexity. Navigation

reasoning concerns spatial reachability, path feasibility, and inter-robot interference, while object interaction involves manipulation-specific preconditions and effects. Jointly inferring these heterogeneous constraints often yields incomplete or inconsistent predicates. By isolating navigation reasoning, LLM_{reach} focuses on identifying accessible locations and feasible robot motions while avoiding conflicts. Grounded in $\mathcal{G}_{\text{reach}}$, which encodes spatial layout and connectivity, this step produces navigation predicates with greater consistency and reliability:

$$\text{Reach} = \text{LLM}_{\text{reach}}(\text{Relation}, \text{Property}, \mathcal{G}_{\text{reach}}). \quad (5)$$

5) Problem PDDL: Finally, the extracted goal, relational structure, object properties, and navigation constraints are integrated to construct the complete PDDL problem. LLM_{PDDL} synthesizes a coherent symbolic representation that reflects both environmental constraints and robot capabilities:

$$\text{ProbPDDL} = \text{LLM}_{\text{PDDL}}(\text{Goal}, \text{Relation}, \text{Property}, \text{Reach}). \quad (6)$$

This structured workflow ensures that each PDDL component is derived from explicitly grounded information rather than implicitly inferred by the LLM. By decomposing the extraction of goals, relationships, properties, and navigability, the approach mitigates common sources of symbolic inconsistency, including missing predicates, invalid preconditions, and incorrect object bindings. As a result, the generated PDDL problem more accurately encodes the environment

state and agent capabilities, yielding executable and semantically coherent plans, as evidenced by the results in Section V.

C. Replanning for Symbolic Execution Failures

Symbolic task planners are highly sensitive to inconsistencies in domain specifications, and even minor inaccuracies in a PDDL description can cause planning failure. In PDDL-based systems, such failures commonly arise from omitted preconditions, affordances, or state transitions. For example, a box may be encoded as `(box, has-state, closed)` while the knowledge graph fails to specify that the box is openable; in this case, the planner cannot generate a valid plan to retrieve the contained object. These failure modes are prevalent in long-horizon manipulation tasks and motivate the need for a robust replanning mechanism that can identify and correct incomplete or inconsistent symbolic representations.

To address these failures, we first diagnose executor exceptions by extracting the error message e , which identifies planner failures (no plan found), execution failures (violated action preconditions), or perception failures (required objects not found). Conditioned on this diagnostic signal, we invoke the iterative refinement framework in Algorithm 1. The LLM proposes a set of hypothesized corrections to the knowledge graph, formalized as

$$\{H_1, \dots, H_k\}, \{\pi_1, \dots, \pi_k\} = \text{LLM}_{\text{replan}}(k, e, \mathcal{G}), \quad (7)$$

where each H_i is a candidate update—such as adding a missing affordance, state, or relational fact—that may resolve the failure, k is the number of candidates, and π_i denotes the model-estimated likelihood of that candidate.

Each hypothesis is evaluated by applying the proposed update to the knowledge graph, regenerating the corresponding PDDL domain and problem, and re-running the planner. If a valid plan is found, we compute the associated plan cost difference Δc_i , with the plan cost defined as the PDDL plan length. Otherwise, the candidate is discarded. Selection is performed using the probability–cost objective:

$$H^* = \arg \max_i \frac{p_i}{(\Delta c_i)^\lambda}, \quad (8)$$

where $p_i = \pi_i / \sum_{j=1}^k \pi_j$ is the normalized candidate probability and λ controls the trade-off between semantic plausibility and minimal symbolic modification.

This refinement loop iterates until a valid plan is obtained or a predefined update budget is exhausted. By tightly coupling failure diagnosis, LLM-guided symbolic repair, and planner-in-the-loop validation, the replanning mechanism enables robust recovery from symbolic inconsistencies and substantially improves reliability in long-horizon manipulation tasks with complex object states and interactions.

D. VLM-Based Discovery under Partial Observability

Due to partial observability, the initial knowledge graph may be incomplete. To address this, we employ a VLM to reason over visual observations upon execution failures or after action completion. The VLM identifies previously unobserved entities and infers their spatial relations, which are converted into semantic tuples and integrated into the

Algorithm 1: KGLAMP Replanning

```

1: Initialize iteration counter  $t \leftarrow 0$ , error  $e$ , number of
   candidates  $k$ , knowledge graph  $\mathcal{G}$ , trade-off coefficient  $\lambda$ ,
   domain  $d$ , problem PDDL  $\text{Prob}_{\text{PDDL}}$ 
2: while  $e \neq \emptyset$  do
3:    $\{H_1, \dots, H_k\}, \{\pi_1, \dots, \pi_k\} \leftarrow \text{LLM}_{\text{replan}}(k, e, \mathcal{G})$  {top- $k$ 
   candidate fixes using current error}
4:   for  $i = 1, \dots, k$  do
5:      $p_i \leftarrow \pi_i / \sum_{j=1}^k \pi_j$  {normalize probabilities}
6:   end for
7:   for  $i = 1$  to  $k$  do
8:      $\mathcal{G}_{\text{temp}}^{(i)} \leftarrow \mathcal{G} \cup H_i$  {update knowledge graph}
9:      $\text{Prob}_{\text{PDDL}, i}^{\text{new}} \leftarrow \text{GENERATEPDDL}(\mathcal{G}_{\text{temp}}^{(i)})$  {get PDDL}
10:     $\text{plan}_i, e_i \leftarrow \text{PLANNER}(d, \text{Prob}_{\text{PDDL}, i}^{\text{new}})$  {get new plan;
    capture new error message if any}
11:    if  $\text{plan}_i$  is valid then
12:       $\Delta c_i \leftarrow \text{cost}(d, \text{Prob}_{\text{PDDL}, i}^{\text{new}}) - \text{cost}(d, \text{Prob}_{\text{PDDL}})$ 
      {change in cost evaluation}
13:    else
14:       $\Delta c_i \leftarrow \infty$ 
15:    end if
16:   end for
17:    $H^* \leftarrow \arg \max_i \frac{p_i}{(\Delta c_i)^\lambda}$  {best candidate selection}
18:    $\mathcal{G} \leftarrow \mathcal{G} \cup H^*$  {updated knowledge graph}
19:    $\text{Prob}_{\text{PDDL}} \leftarrow \text{GENERATE PDDL}(\mathcal{G})$  {get final PDDL}
20:    $\text{plan}, e \leftarrow \text{PLANNER}(d, \text{Prob}_{\text{PDDL}})$  {get updated plan}
21: end while
22: return  $\mathcal{G}, \text{Prob}_{\text{PDDL}}, \text{plan}$ 

```

knowledge graph. These updates support dynamic replanning, enabling the symbolic executor to ground the PDDL problem in newly discovered environmental information and recover from incomplete world states.

V. EXPERIMENTS

In this section, we provide details of our experiments.

A. Dataset

We evaluate our framework on the MAT-THOR benchmark [11], a multi-agent long-horizon task dataset built on AI2-THOR [32]. MAT-THOR comprises 51 indoor multi-robot planning tasks across seven floor plans, grouped into three categories: (i) 25 *Simple Tasks* with one to two subgoals and short horizons (e.g., “Open the laptop and turn it on.”); (ii) 19 *Complex Tasks* requiring coordinated execution by heterogeneous robots over longer horizons (e.g., “Slice the lettuce, trash the mug, and switch off the light.”); and (iii) 7 *Vague Command Tasks* with underspecified natural language instructions (e.g., “Prepare ingredients for cooking a sandwich tomorrow.”)

B. Qualitative Analysis: Symbolic Replanning

An example of how replanning improves robustness is illustrated in Fig. 6 using a qualitative example: *Put the watch and keychain inside the drawer*. The goal is encoded as `(watch, in, drawer)` and `(keychain, in, drawer)`. Execution of the initial plan fails because the symbolic model omits the physical precondition that the drawer must be open to satisfy



Fig. 6: Qualitative example of planning and replanning. In the task *Put the watch and keychain inside the drawer*, the robot fails when placing the watch into a closed drawer. It recovers by replanning to open the drawer and completes the task.

the *inside* relation, causing failure at *Action 3* when placing the watch. The system attributes the failure to a missing precondition, updates the knowledge graph accordingly, and inserts a corrective drawer-opening action. The repaired plan then executes successfully, demonstrating the framework’s ability to recover via symbolic replanning.

C. Evaluation Metrics and Baselines

We utilize five evaluation metrics that capture task success, action validity, and temporal efficiency. *Task Completion Rate (TCR)* measures the percentage of tasks in which all goal conditions are satisfied. *Goal Condition Recall (GCR)* quantifies the proportion of ground-truth goal conditions achieved in the final state. *Executability Rate (ER)* reports the percentage of planned actions that are successfully executed in the simulator, independent of task relevance. *Planning Time (PT)* denotes the time required to generate the final multi-robot plan, while *Execution Time (ET)* measures the time to execute the plan in AI2-THOR. Together, these metrics are widely used in the literature [11], [19] and assess correctness, robustness, and operational efficiency.

We compare against four representative baselines. *LLM-as-Planner* [33] treats the language model as a standalone planner that directly generates action sequences without structural constraints or verification. *LLM-as-Planner with Chain-of-Thought (CoT)* [34] elicits explicit reasoning before plan generation, with plans manually converted into executable actions. *LLM+P* [6] adds a post-hoc execution-phase validator that detects invalid actions but provides no planning-time guidance. Finally, *LaMMA-P* [11] incorporates structured knowledge and adaptive multi-agent reasoning to improve plan coherence and execution reliability. We set $\lambda = 2$ and a 300-second planning time limit, and use GPT-5 [35] for all methods to ensure a fair comparison.

D. Performance in Full Knowledge Graph

As shown in Table I, our method achieves the highest task success rate among all baselines, outperforming the strongest competitor, *LaMMA-P*, by 25.5% across all 51 tasks¹. We

¹We re-ran LaMMA-P on the publicly available MAT-THOR release and observed discrepancies in absolute performance metrics compared to those reported in the original paper. After discussions with the LaMMA-P authors, we attribute these differences to variations in dataset version and size, as well as differences in the experimental setup. To ensure a fair comparison, we evaluate all methods using the same released benchmark configuration.

compare against three categories of methods. The first includes *LLM-as-Planner* and *LLM-as-Planner + CoT*, which directly generate action sequences from task descriptions. Although these approaches exhibit low inference latency, they consistently struggle with complex, long-horizon, or vague tasks due to error accumulation and the lack of explicit grounding in environmental structure and constraints.

The second category, *LLM+P*, uses an LLM to interpret the environment, generate a PDDL problem, and delegate planning to a classical planner. While effective on some tasks when the PDDL formulation is accurate, it often fails in practice due to the difficulty of producing syntactically and semantically valid plans. Errors or omissions—such as incorrect predicates, action schemas, or object definitions—frequently lead to planner failure or infeasible plans.

The third category, *LaMMA-P*, introduces explicit task decomposition, translating each subtask into a separate PDDL problem. Although this improves scalability, it does not explicitly model inter-agent coordination or object-level dependencies across subtasks. Consequently, when task preconditions depend on other agents’ actions or shared object states, the resulting plans can be inconsistent or incomplete.

In contrast, our method formulates each task within a unified framework that jointly coordinates all robots while explicitly modeling object-level dependencies. By leveraging a comprehensive knowledge graph capturing semantic, spatial, and relational structure, the system enables grounded reasoning and reliable execution, yielding the highest overall success rate across the evaluation tasks.

E. Ablation Study

As shown in Table II, the ablation results indicate that each system component plays a critical, non-redundant role in robust task performance. Removing any individual module reduces success, while progressively eliminating graph-based representations causes substantial degradation. In particular, removing all graph structures yields the largest drop, underscoring the importance of structured semantic, property, and relational information for guiding manipulation.

Specifically, $\mathcal{G}_{\text{property}}$ provides semantic cues identifying which objects must be manipulated to accomplish the task, $\mathcal{G}_{\text{relation}}$ encodes object-specific affordances required for selecting appropriate manipulation strategies, and $\mathcal{G}_{\text{reach}}$ enforces spatial and relational consistency to support correct coordinate-frame reasoning and collision avoidance. Complementing these components, the replanning mechanism further enhances robustness by enabling recovery from execution failures and partial observability, such as when a target object is initially enclosed and must first be exposed. Collectively, these results confirm that the full system configuration is necessary to maximize reliability and efficiency, with each component contributing uniquely to overall performance.

F. Task Planning under Partial Observability

To evaluate robustness under environmental uncertainty, we consider partial observability by omitting 12 critical objects (e.g., *Tomato*, *Laptop*) from the initial world model,

Method	Basic					Complex					Vague				
	TCR(%)	GCR(%)	ER(%)	PT(s)	ET(s)	TCR(%)	GCR(%)	ER(%)	PT(s)	ET(s)	TCR(%)	GCR(%)	ER(%)	PT(s)	ET(s)
LLM-as-Planner	32.0	44.0	76.0	32.6	45.0	10.5	22.8	69.8	39.9	55.9	14.3	21.4	12.1	53.5	106.6
LLM-as-Planner (CoT)	36.0	44.0	77.2	27.6	54.0	26.3	46.5	77.9	36.9	69.2	14.3	21.4	35.7	43.1	35.2
LLM + P	20.0	36.0	60.1	61.1	35.4	15.8	32.4	15.9	83.1	52.6	0.0	0.0	0.0	10.7	0.0
LaMMA-P	60.0	74.0	90.0	131.8	114.8	36.8	60.1	74.3	190.9	163.9	57.1	57.1	63.7	167.7	199.0
Ours w/o replan	72.0	80.0	91.3	171.4	95.5	47.4	52.6	68.9	236.6	89.4	57.1	57.1	92.9	169.1	172.2
Ours	84.0	85.2	97.5	181.7	67.7	68.4	60.3	94.9	284.3	144.8	71.4	71.4	94.3	301.5	77.4

TABLE I: Performance comparison across methods.

Method	TCR(%)	GCR(%)	ER(%)	PT(s)	ET(s)
Ours	76.5	74.0	96.1	236.4	97.75
Ours w/o replan	60.7	60.2	83.1	195.4	103.7
Ours w/o \mathcal{G}_{reach}	58.8	64.7	83.8	181.7	99.0
Ours w/o \mathcal{G}_{reach} and $\mathcal{G}_{property}$	52.9	60.2	80.6	156.5	83.7
Ours w/o \mathcal{G}_{reach} , $\mathcal{G}_{property}$ and $\mathcal{G}_{relation}$	37.2	48.4	68.6	95.6	76.8

TABLE II: Ablation results with different graph structures.

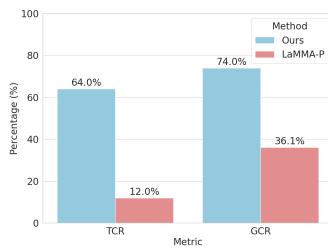


Fig. 7: Performance Comparison under partial observability where 12 critical objects are omitted from the initial knowledge graph.

requiring VLM-driven object discovery and replanning. As shown in Fig. 7, our method achieves a TCR of 64.0% and a GCR of 74.0%, substantially outperforming *LaMMA-P*, which attains a TCR of 12.0% and a GCR of 36.1% due to plan inconsistency.

These results demonstrate the effectiveness of our replanning mechanism in dynamically updating the knowledge graph as new entities are perceived. The remaining gap relative to full-observability settings highlights challenges in active perception, where VLM recognition errors and suboptimal viewpoints can hinder reliable object identification in cluttered scenes. Despite these limitations, integrating VLM feedback into graph-based planning yields significantly more robust long-horizon task execution than existing baselines.

G. Local Environment Model Comparison

We evaluate several open-source language models in a controlled local setting using the `ollama` framework. All experiments are conducted on an Ubuntu 22.04 workstation with an AMD Ryzen Threadripper 7960X CPU, 128 GB RAM, and an NVIDIA GeForce RTX 5080 GPU. The evaluated models include Llama 3.2 3B [36], Phi 3 Mini 7B [37], Mistral 7B [38], and Qwen 2 7B [39]. As shown in Table III, the models exhibit broadly similar performance across tasks. Qwen 2 7B achieves the strongest results, with a 5.8% higher TCR than Llama 3.2, though the gap remains modest, indicating limited sensitivity to model choice under identical hardware and runtime conditions.

Inference efficiency is also comparable, with all models achieving response times under 25 seconds, demonstrating that locally deployed lightweight models can provide practical responsiveness without specialized infrastructure.

Method	TCR(%)	GCR(%)	ER(%)	PT(s)	ET(s)
llama3.2 3B	39.2	53.3	71.0	24.9	67.5
phi3:mini 7B	41.2	53.3	72.9	13.9	86.4
mistral 7B	41.2	54.9	73.0	16.5	59.6
qwen2:7B	45.0	56.9	73.2	18.8	80.5

TABLE III: Performance comparison across models.

Their relatively small parameter counts (3B–7B) as compared to frontier-scale models like GPT-5 (>100B parameters), contribute to efficient execution. Notably, none of the evaluated models are explicitly optimized for complex reasoning, which may limit their performance on some benchmarks.

VI. CONCLUSION

We presented *KGLAMP*, a knowledge-graph-guided LLM planning framework for long-horizon planning in heterogeneous multi-robot systems. By grounding planning in unified structured graphs encoding object relations, spatial reachability, and robot capabilities, *KGLAMP* enables LLMs to generate task representations that better reflect real-world constraints. Experiments show that *KGLAMP* substantially outperforms LLM-only and PDDL-based baselines, achieving a 25.5% improvement in task completion rate and a 15.5% reduction in execution failures relative to the strongest baseline across all tasks. Moreover, incremental knowledge-graph updates improve robustness by enabling adaptation to incomplete or evolving environment information, maintaining performance in dynamic settings.

Overall, *KGLAMP* demonstrates that coupling LLM-based reasoning with structured, continuously updated knowledge representations is a promising direction for reliable, scalable, and context-aware planning in heterogeneous multi-robot teams. Future work will explore deployment on physical robots, training smaller distilled models via knowledge distillation [40], tighter integration with perception and feedback loops, and scaling to increasingly unstructured environments.

VII. LIMITATIONS

Despite its effectiveness, our approach has several limitations. First, it relies on sufficiently detailed environmental and task information to construct the knowledge graph; while LLMs can infer missing attributes, such inference may introduce noise or inconsistencies. Second, coordinating multiple LLM components incurs significant computational overhead, limiting scalability for real-time or large-scale deployment. Third, even with explicitly specified domain symbols and type definitions, general-purpose LLMs may generate PDDL predicates or action schemas that violate syntactic or semantic constraints, yielding invalid planning domains without additional verification or correction mechanisms.

REFERENCES

- [1] Yulun Zhang, Matthew C Fontaine, Varun Bhatt, Stefanos Nikolaidis, and Jiaoyang Li. Multi-robot coordination and layout design for automated warehousing. In *Proceedings of the International Symposium on Combinatorial Search*, volume 17, pages 305–306, 2024.
- [2] Ruofei Bai, Ronghao Zheng, Meiqin Liu, and Senlin Zhang. Multi-robot task planning under individual and collaborative temporal logic specifications. In *International Conference on Intelligent Robots and Systems (IROS)*, pages 6382–6389. IEEE, 2021.
- [3] Piyush Gupta, Shaunak D Bopardikar, and Vaibhav Srivastava. Incentivizing collaboration in heterogeneous teams via common-pool resource games. *IEEE Transactions on Automatic Control*, 68(3):1902–1909, 2022.
- [4] Piyush Gupta, Shaunak D Bopardikar, and Vaibhav Srivastava. Achieving efficient collaboration in decentralized heterogeneous teams using common-pool resource games. In *58th Conference on Decision and Control (CDC)*, pages 6924–6929. IEEE, 2019.
- [5] Ruihai Liu, Guangxi Wan, Maowei Jiang, Haojie Chen, and Peng Zeng. Autonomous robot task execution in flexible manufacturing: Integrating PDDL and behavior trees in ARIAC 2023. *Biomimetics*, 9(10):612, 2024.
- [6] Bo Liu, Yuqian Jiang, Xiaohan Zhang, Qiang Liu, Shiqi Zhang, Joydeep Biswas, and Peter Stone. LLM+P: Empowering large language models with optimal planning proficiency. *arXiv preprint arXiv:2304.11477*, 2023.
- [7] Allen Z Ren, Anushri Dixit, Alexandra Bodrova, Sumeet Singh, Stephen Tu, Noah Brown, Peng Xu, Leila Takayama, Fei Xia, Jake Varley, et al. Robots that ask for help: Uncertainty alignment for large language model planners. *arXiv preprint arXiv:2307.01928*, 2023.
- [8] Lin Guan, Karthik Valmecikam, Sarah Sreedharan, and Subbarao Kambhampati. Leveraging pre-trained large language models to construct and utilize world models for model-based task planning. *Advances in Neural Information Processing Systems*, 36:79081–79094, 2023.
- [9] David Bai, Ishika Singh, David Traum, and Jesse Thomason. TWOSTEP: Multi-agent task planning using classical planners and large language models. *arXiv preprint arXiv:2403.17246*, 2024.
- [10] Barbara Arbanas Ferreira, Tamara Petrović, Matko Orsag, J Ramiro Martínez-de Dios, and Stjepan Bogdan. Distributed allocation and scheduling of tasks with cross-schedule dependencies for heterogeneous multi-robot teams. *IEEE access*, 12:74327–74342, 2024.
- [11] Xiaopan Zhang, Hao Qin, Fuquan Wang, Yue Dong, and Jiachen Li. LaMMA-P: Generalizable multi-agent long-horizon task allocation and planning with LM-driven PDDL planner. In *International Conference on Robotics and Automation*, pages 10221–10221. IEEE, 2025.
- [12] Liancheng Gong, Wang Zhu, Jesse Thomason, and Li Zhang. Zero-shot iterative formalization and planning in partially observable environments. *arXiv preprint arXiv:2505.13126*, 2025.
- [13] Shivam Goel, Yichen Wei, Panagiotis Lympertopoulos, Klára Churá, Matthias Scheutz, and Jivko Sinapov. NOVELGYM: A flexible ecosystem for hybrid planning and learning agents designed for open worlds. *arXiv preprint arXiv:2401.03546*, 2024.
- [14] Haoqiang Kang, Enna Sachdeva, Piyush Gupta, Sangjae Bae, and Kwonjoon Lee. GFlowVLM: Enhancing multi-step reasoning in vision-language models with generative flow networks. In *Proceedings of the Computer Vision and Pattern Recognition Conference*, pages 3815–3825, 2025.
- [15] Piyush Gupta, David Isele, Enna Sachdeva, Pin-Hao Huang, Behzad Dariush, Kwonjoon Lee, and Sangjae Bae. Generalized mission planning for heterogeneous multi-robot teams via LLM-constructed hierarchical trees. In *2025 IEEE International Conference on Robotics and Automation (ICRA)*, pages 10187–10193, 2025.
- [16] Yue Cao and CS Lee. Robot behavior-tree-based task generation with large language models. *arXiv preprint arXiv:2302.12927*, 2023.
- [17] Haoqi Yuan, Chi Zhang, Hongcheng Wang, Feiyang Xie, Penglin Cai, Hao Dong, and Zongqing Lu. Skill reinforcement learning and planning for open-world long-horizon tasks. *arXiv preprint arXiv:2303.16563*, 2023.
- [18] Lutfi Eren Erdogan, Nicholas Lee, Sehoon Kim, Suhong Moon, Hiroki Furuta, Gopala Anumanchipalli, Kurt Keutzer, and Amir Gholami. PLAN-AND-ACT: Improving planning of agents for long-horizon tasks. *arXiv preprint arXiv:2503.09572*, 2025.
- [19] Shyam Sundar Kannan, Vishnunandan LN Venkatesh, and Byung-Cheol Min. Smart-LLM: Smart multi-agent robot task planning using large language models. In *2024 IEEE/RSJ International Conference on Intelligent Robots and Systems*, pages 12140–12147. IEEE, 2024.
- [20] Piyush Gupta, Sangjae Bae, and David Isele. Graph-grounded LLMs: Leveraging graphical function calling to minimize LLM hallucinations. *arXiv preprint arXiv:2503.10941*, 2025.
- [21] Fangru Lin, Emanuele La Malfa, Valentin Hofmann, Elle Michelle Yang, Anthony Cohn, and Janet B Pierrehumbert. Graph-enhanced large language models in asynchronous plan reasoning. *arXiv preprint arXiv:2402.02805*, 2024.
- [22] Zhehui Huang, Guangyao Shi, Yuwei Wu, Vijay Kumar, and Gaurav S Sukhatme. Compositional coordination for multi-robot teams with large language models. *arXiv preprint arXiv:2507.16068*, 2025.
- [23] Kehui Liu, Zixin Tang, Dong Wang, Zhigang Wang, Xuelong Li, and Bin Zhao. COHERENT: Collaboration of heterogeneous multi-robot system with large language models. In *International Conference on Robotics and Automation*, pages 10208–10214. IEEE, 2025.
- [24] Yanfang Zhou, Xiaodong Li, Yuntao Liu, Yongqiang Zhao, Xintong Wang, Zhenyu Li, Jinlong Tian, and Xinhai Xu. M2PA: A multi-memory planning agent for open worlds inspired by cognitive theory. In *Findings of the Association for Computational Linguistics: ACL 2025*, pages 23204–23220, 2025.
- [25] Tomoyuki Kagaya, Thong Jing Yuan, Yuxuan Lou, Jayashree Karlekar, Sugiri Pranata, Akira Kinose, Koki Oguri, Felix Wick, and Yang You. RAP: Retrieval-augmented planning with contextual memory for multimodal LLM agents. *arXiv preprint arXiv:2402.03610*, 2024.
- [26] Abrar Anwar, John Welsh, Joydeep Biswas, Soha Pouya, and Yan Chang. REMEMBER: Building and reasoning over long-horizon spatio-temporal memory for robot navigation. In *International Conference on Robotics and Automation*, pages 2838–2845. IEEE, 2025.
- [27] Zaijing Li, Yuquan Xie, Rui Shao, Gongwei Chen, Dongmei Jiang, and Liqiang Nie. OPTIMUS-1: Hybrid multimodal memory empowered agents excel in long-horizon tasks. *Advances in neural information processing systems*, 37:49881–49913, 2024.
- [28] Zixuan Wang, Bo Yu, Junzhe Zhao, Wenhao Sun, Sai Hou, Shuai Liang, Xing Hu, Yinhe Han, and Yiming Gan. KARMA: Augmenting embodied ai agents with long-and-short term memory systems. In *International Conference on Robotics and Automation*, pages 1–8. IEEE, 2025.
- [29] Krish Agarwal, Yuqian Jiang, Jiaheng Hu, Bo Liu, and Peter Stone. L3M+ P: Lifelong planning with large language models. *arXiv preprint arXiv:2508.01917*, 2025.
- [30] Diego Aineto, Sergio Jiménez, and Eva Onaindia. Learning STRIPS action models with classical planning. In *Proceedings of the International Conference on Automated Planning and Scheduling*, volume 28, pages 399–407, 2018.
- [31] Malte Helmert. The fast downward planning system. *Journal of Artificial Intelligence Research*, 26:191–246, 2006.
- [32] Eric Kolve, Roozbeh Mottaghi, Winson Han, Eli VanderBilt, Luca Weihs, Alvaro Herrasti, Matt Deitke, Kiana Ehsani, Daniel Gordon, Yuke Zhu, et al. AI2-THOR: An interactive 3D environment for visual AI. *arXiv preprint arXiv:1712.05474*, 2017.
- [33] Zihao Zhou, Bin Hu, Chenyang Zhao, Pu Zhang, and Bin Liu. Large language model as a policy teacher for training reinforcement learning agents. *arXiv preprint arXiv:2311.13373*, 2023.
- [34] Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35:24824–24837, 2022.
- [35] OpenAI. GPT-5. <https://openai.com/gpt-5/>, 2025. Accessed: 2025-12-03.
- [36] Llama Team, AI @ Meta. The Llama 3 herd of models, 2024.
- [37] Marah Abdin, Jyoti Aneja, Harkirat Behl, Sébastien Bubeck, Ronen Eldan, Suriya Gunasekar, Michael Harrison, Russell J Hewett, Mojtaba Javaheripi, Piero Kauffmann, et al. Phi-4 technical report. *arXiv preprint arXiv:2412.08905*, 2024.
- [38] Albert Q. Jiang, Alexandre Sablayrolles, Antoine Roux, et al. Mistral 7b, 2023.
- [39] An Yang, Baosong Yang, Binyuan Hui, et al. Qwen2 technical report, 2024.
- [40] Piyush Gupta, David Isele, and Sangjae Bae. Towards scalable & efficient interaction-aware planning in autonomous vehicles using knowledge distillation. In *2024 IEEE Intelligent Vehicles Symposium (IV)*, pages 2735–2742. IEEE, 2024.