Hierarchical Task Network Planning with LLM-Generated Heuristics

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Abstract

HTN planning is a variation of classical planning where, instead of searching for a linear sequence of actions, an algorithm decomposes higher-level tasks using a method library until only executable actions remain. On one hand, this allows one to introduce domain knowledge that can speed up the search for a solution through the method library. On the other hand, it creates challenges that go beyond those of classical state-space search. While recent research produced a number of heuristics and novel algorithms that speed up HTN planning, these heuristics are not yet as informative as those available in classical planning algorithms. We investigate whether large language models (LLMs) can generate effective search heuristics for HTN planning, extending the methodology of Corrêa et al. [5] from classical to hierarchical planning. Using the PYTRICH planner on six standard total-order HTN benchmark domains, we evaluate heuristics generated by nine LLMs under domain-specific prompting and compare them against the TDG and LMCOUNT domain-independent baselines and the PANDA planner. Our results show that LLM-generated heuristics nearly match the coverage of the best available HTN planner, while substantially reducing search effort on 83% of shared problems.

1 Introduction

Hierarchical Task Network (HTN) planning [6, 7, 4] is a widely used formalism for structured, goal-directed tasks in robotics, game AI, and intelligent assistants. Unlike classical planning, which searches over state transitions, HTN planning decomposes abstract tasks into sequences of primitive actions through ***methods***, requiring search over a joint space of world states and task networks. The decomposition hierarchy encodes domain knowledge directly, playing the role that explicit heuristics serve in classical planning: it constrains which actions the algorithm tries and in what order, without requiring a domain-independent estimate of goal distance. This richer structure makes HTN planning substantially harder to scale without effective search guidance. HTN planning is useful in this setting because many domains describe work as procedures rather than as a flat set of goal facts. A robot mission, for example, may choose a survey, delivery, or repair procedure before expanding it into navigation, sensing, and manipulation steps; game agents and assistants use similar routines. A classical encoding can represent the same primitive actions, but it often pushes procedural knowledge into extra predicates, control rules, or a large compiled model. HTN models keep this knowledge explicit in tasks and methods, giving the LLM structured domain information that it can turn into search guidance. Domain-independent heuristics offer guidance without requiring hand-crafted, domain-specific knowledge; the established methods include an admissible relaxation heuristic [3], a compilation of the HTN search state into a classical planning problem that enables reuse of classical heuristics such as FF and LMCUT [12, 14], the Task Decomposition Graph (TDG)

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heuristic [15], and landmark-based counting (LMCOUNT) [11, 21]. Despite these advances, the field has moved slowly: the winner of the 2020 International Planning Competition for HTN planning was HYPERTENSION[18], a planner that relies on efficient recursive search and bookkeeping rather than an explicit heuristic function, suggesting that domain-independent HTN heuristics had not yet delivered decisive practical advantage.

Recent work shows that large language models (LLMs) can generate effective heuristic functions for classical planning as code [5]. The methodology prompts an LLM with domain context, evaluates candidate heuristics on training problems, selects the best performer, and deploys it on unseen test problems. The resulting heuristics outperform established domain-independent baselines and rival domain-specific methods, a striking result given the absence of any explicit heuristic engineering. Extending this methodology to HTN planning poses additional challenges. A heuristic for HTN search must reason not only over the world state but also over the current ***task network***: the set of pending tasks, their ordering constraints, and the applicable decomposition methods. An LLM must therefore grasp hierarchical decomposition semantics to produce useful guidance, a harder task than reasoning over state-only features. Thus, this paper adapts the LLM heuristic generation methodology of Corrêa et al. [5] to total-order HTN planning, with the following contributions.

1. We implement the generate-evaluate-select pipeline within the PYTRICH planner [21] and define a Python heuristic interface that exposes HTN state and task-network information to the LLM (Section 3).
2. We evaluate heuristics generated by nine LLMs under domain-specific prompting across six benchmark domains from the International Planning Competition (IPC) 2020 HTN planning track, covering three search algorithms (A*, GBFS, and Weighted A*) (Section 4).
3. We show that the virtual best over all LLM models and algorithms nearly matches the PANDA planner in coverage, while substantially reducing search effort on 83% of shared instances (Section 5).
4. We identify which LLM models contribute most to coverage and how the choice of search algorithm interacts with heuristic quality (Section 5).

2 HTN Planning

An HTN planning problem is a tuple $\mathcal{P}_{\text{HTN}} = \langle s_0, \omega_I, F, A, C, \mathcal{M} \rangle$, where F is a set of ground fluents, A is a set of primitive actions with preconditions and effects over F, C is a set of compound tasks, $\mathcal{M}$ is a set of methods, ω_I is the initial task network, and $s_0 \subseteq F$ is the initial state [6, 7, 21]. A ***task network*** $\omega = \langle T, \prec, \alpha \rangle$ consists of a finite set of task identifiers T, a strict partial order $\prec$ over T encoding ordering constraints, and a labelling function $\alpha : T \to A \cup C$ that assigns each identifier to a primitive action or compound task. A ***method*** $m = \langle c, \omega_m \rangle \in \mathcal{M}$ decomposes a compound task $c \in C$ into a subnetwork ω_m; applying m replaces the occurrence of c in the current network with ω_m. A ***solution*** is a sequence of primitive actions obtained by repeatedly selecting and decomposing compound tasks until the network contains only primitive tasks, such that the resulting sequence is executable from s_0.

This paper considers ***total-order*** HTN planning, in which every task network imposes a strict linear order on its tasks. Total-order HTN is widely studied [4] and is the setting used in the IPC 2020 HTN planning track [1], which supplies the domains and problems for our evaluation. Our evaluation uses problems encoded in HDDL [13], the standard input language for HTN planners. We use the PYTRICH planner [21] as our experimental platform because it exposes a clean Python interface for plugging in custom heuristic functions, making it straightforward to deploy LLM-generated code.

2.1 Domain-Independent Heuristics for HTN Planning

The TDG heuristic [3] estimates the cost to solve the current task network by computing a relaxed reachability bound over the Task Decomposition Graph, a precomputed structure that encodes which primitive actions can arise from each compound task. It ignores delete effects and ordering constraints, yielding an admissible but often weak estimate.

Landmark-based counting (LMCOUNT) [11] extracts ***landmarks***, facts or tasks that must occur on every solution path, from the task network structure. The heuristic value is the count of landmarks not yet achieved. Putrich et al. [21] extend this approach by identifying additional landmarks, improving guidance while preserving polynomial extraction time.

Both heuristics are domain-independent: they exploit only the syntactic structure of the HDDL encoding and require no user-supplied domain knowledge. They serve as the primary algorithmic baselines in our evaluation; we additionally compare against the PANDA planner [2, 3], which incorporates a family of reachability-based heuristics and represents the strongest available complete HTN system.

3 LLM-Generated Heuristics for HTN Planning

Corrêa et al. [5] show that LLMs can serve as heuristic engineers for classical planning. Their methodology asks an LLM to write a Python function that maps a planning state to a numeric estimate of the distance to the goal. A batch of candidate functions is generated by prompting the model with the domain encoding and a description of the heuristic interface; candidates that raise exceptions or time out are discarded. The survivors are evaluated on a set of training problems and the one that minimises node expansions is selected for deployment on unseen test problems. Their pipeline is model-agnostic: different LLMs produce heuristics of varying quality, and the selection step acts as an automatic filter that retains only the most effective candidate.

Adapting this methodology to HTN planning requires two changes. First, the heuristic function must accept a task network in addition to the world state, since the remaining work is defined by the pending tasks and their decomposition structure rather than by a goal condition over fluents alone. Second, the LLM must reason about the hierarchical semantics of the domain: which compound tasks remain, how they may be decomposed, and whether the current ordering of tasks suggests a long or short path to completion. These demands are qualitatively harder than reasoning over flat state features, making HTN planning a more challenging test for LLM-generated heuristics.

3.1 Heuristic Function Interface

PYTRICH exposes a Python `Heuristic` base class with two required methods. The initialization method is called once before search and is used for preprocessing; the evaluation method is called at every expansion and must return a non-negative estimate of remaining solution cost. This split is important for runtime: expensive operations can be moved to initialization to amortize their costs, keeping per-node evaluation lightweight.

The interface also exposes both parts of an HTN search state. From `model`, the heuristic receives grounded domain structure (facts, primitive operators, abstract tasks, decomposition methods, and goals). From `node`, it receives the current state and the remaining task network. In particular, states and operator conditions are represented as bitsets, which enables constant-time fact checks and efficient relaxed computations.

The most important distinction from the classical planning interface of Corrêa et al. [5] is explicit access to the HTN-specific task network: the pending abstract tasks and the decomposition methods applicable to each. A heuristic that ignores the task network degenerates to a classical-planning heuristic and loses all HTN-specific guidance; exploiting this structure is the central challenge the LLM must address to produce useful estimates. We include a detailed explanation of the API in Appendix F for reproducibility.

3.2 Prompt Design

We use a domain-specific prompt regime in which the LLM receives the domain name, the full domain HDDL file, the smallest and largest training problem instances, a worked example of a correct heuristic implementation, and a per-domain hint block. The prompt directs the LLM through four steps: identify the planning bottleneck by determining which compound tasks decompose into many primitives; list two or three independent admissible lower bounds and combine them via `max`; implement the result using the two-method interface, keeping the per-node evaluation O(1) by moving all loops to the preprocessing step; and add subunit tie-breaking penalties for symmetric states, which preserve admissibility while breaking symmetries.

Several technical details require explicit treatment in the prompt because LLMs otherwise default to incorrect conventions when working with PYTRICH. The format of grounded fact names differs from HDDL predicate syntax, and the prompt illustrates this difference with wrong-versus-right examples. The prompt also specifies how to query goal facts via the bitwise state encoding, provides correct import paths for the heuristic base class and model types, and gives full method signatures with type annotations. The prompt asks the LLM to return its response in a structured, parseable format so that candidates can be saved without additional text processing.

Following Corrêa et al. [5], we use a standardized per-domain hint block with three components: (i) representation caveats introduced by grounding, (ii) the dominant domain-specific search bottleneck, and (iii) heuristic-construction guidance, including lower-bound candidates, symmetry-breaking features, and empirically meaningful penalty scales. The block is descriptive rather than prescriptive: it reduces interface and domain-interpretation errors but leaves heuristic formulation to the model. Like Corrêa et al., we use iterative failure analysis from early experiments to refine the hints block. But unlike their fully hand-written checklist, in our pipeline, this refinement is LLM-assisted, with the model summarizing failure modes and proposing the next hint revision. All quantitative results in this paper use this hinted condition; we leave a direct comparison to a hint-free condition for future work. Details and examples are reported in Appendix B.

We also implement an iterative refinement variant that augments the base prompt with the previous candidate code, its empirical results against the TDG baseline (expanded nodes, wall time, solution length, and exit status), and auto-generated guidance keyed to the observed failure mode. A candidate that times out receives advice to move all computation to the preprocessing step; a candidate that performs worse than TDG receives advice to add state-awareness or to aggregate decomposition costs across the full task network. The full prompt text and the refinement template are reproduced in Appendix A.

3.3 Heuristic Selection

For each domain and each LLM model, we generate $N = 20$ candidate heuristics in batch mode: twenty independent one-shot invocations of the domain-specific prompt with no feedback between rounds. Each candidate runs on the smallest benchmark problem for the domain under a 60-second wall-clock timeout. We discard candidates that fail to parse, raise runtime exceptions, exceed memory limits, or time out. Among the survivors, we select the candidate that minimises expanded nodes on the training problem, breaking ties in favour of the shorter solution.

We then evaluate the selected candidate without modification on all benchmark problems for that domain, including the selection instance itself. The selection criterion is model-agnostic: it requires only that the heuristic run without error and produce a result on the single training instance, and it does not reward interpretability. This design means that a weaker model contributing just one viable heuristic can still improve the virtual best over all models, and the selection step acts as an automatic quality filter without requiring the experimenter to implement heuristic code.

We leave a systematic evaluation of the iterative refinement variant to future work; all quantitative results in Section 5 use heuristics generated by the base one-shot prompt.

4 Experimental Setup

We briefly describe the main points of our experimental setup next. Appendix C contains more details, such as specific LLM versions, parameters, and resources used.

Domains. We evaluate on six total-order HTN benchmark domains from the IPC 2020 HTN planning track [1], all encoded in HDDL [13]. Table 1 lists each domain and the number of benchmark problems in the *Probs.* column.

Models. We evaluate nine LLMs spanning three providers: Claude Opus 4, Claude Sonnet 4.5, Gemini 2.0 Flash, Gemini 2.5 Pro, Gemini 3 Flash, Gemini 3 Pro, GPT-4o, GPT-5, and GPT-5.2. For each domain-model pair, we generate heuristic candidates using provider-default sampling and evaluate them under the protocol of Section 3.3. A list of models, generation settings, and model-specific failure accounting are reported in Appendix C; summary failure analysis appears in Section 5.3. We compare LLM-generated heuristics against three baselines.

Baseline Planners and Heuristics. The TDG heuristic [15], implemented in PYTRICH, estimates remaining cost by propagating costs bottom-up through a precomputed AND/OR graph: primitive actions receive cost zero and the cost of each compound task is the minimum cost over its decomposition methods, giving a heuristic value at any node equal to the sum of these precomputed costs over the tasks remaining in the task network. PANDA $\mathrm{RC}^{\mathrm{FF}}$ [2, 3, 15] uses a delete-relaxed planning graph as its classical subcomponent; the notation RC^{X} denotes PANDA's family of reachability-based HTN heuristics, where the superscript identifies the classical estimator used to bound the cost of reaching goal conditions from the current state, and $\mathrm{RC}^{\mathrm{FF}}$ uses the FF relaxation [10]. PANDA $\mathrm{RC}^{\mathrm{LMCut}}$ [15] replaces the classical subcomponent with LMCut [9], which produces an admissible estimate by iteratively extracting cost-saturated landmark cuts from the relaxed planning graph; it yields tighter bounds than $\mathrm{RC}^{\mathrm{FF}}$ on individual nodes but at higher per-node cost, and in our benchmark it achieves lower overall coverage (113 vs. 134 problems solved). We apply the same virtual-best treatment to both PANDA baselines as to LLM heuristics (described next).

Search Algorithms. We evaluate each LLM-generated heuristic and each PYTRICH baseline under three search algorithms: Standard A* ($f = g + h$), Greedy Best-First Search (GBFS, $f = h$ only, favouring nodes with the lowest heuristic value), and Weighted A* (WA*, $f = g + 5 \cdot h$, trading plan-optimality for faster search). For each system we report the *virtual best* over these three algorithms: a problem counts as solved if any algorithm finds a solution, and we record the node count from the algorithm that solves it with fewest expansions. This reflects a realistic deployment scenario in which one can choose the search algorithm freely. Results disaggregated by algorithm appear in Section 5.

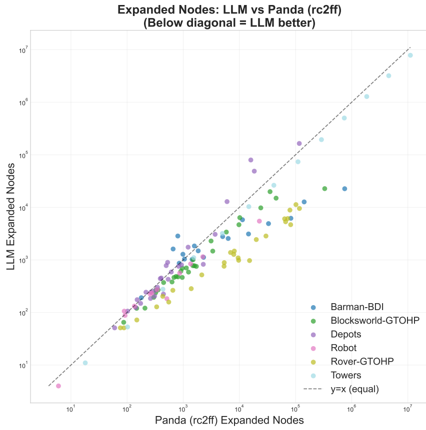
Evaluation Metrics and Resources. We report three metrics. *Coverage* is the number of benchmark problems we solve within the time and memory limits; it is the primary metric, reported per domain and in aggregate. *Node expansions* is the number of search nodes expanded before finding a solution; lower is better, as it measures heuristic guidance quality independently of hardware speed. We report the median over solved problems and head-to-head win counts on the common set of problems solved by both compared systems. *Plan length* is the number of primitive actions in the returned solution; we report head-to-head comparisons on the common solved set. We run our experiments with 8 GB RAM and a 30-minute runtime limit per problem. All runs use 1 CPU core. We run PANDA experiments under identical resource constraints using the pre-compiled `pandaPIengine` binary; additional execution details are provided in Appendix C.

5 Results

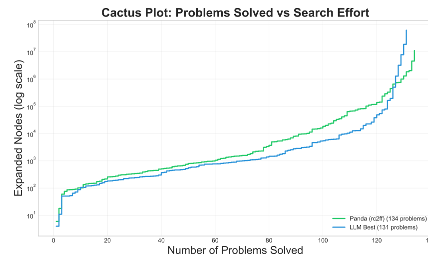
5.1 Coverage

Table 1 reports per-domain and aggregate coverage for all systems. All columns report the virtual best over three search algorithms (GBFS, A, WA). LLM coverage is the virtual best over the five main models; PANDA is shown as two separate engines ($\mathrm{RC}^{\mathrm{FF}}$ and $\mathrm{RC}^{\mathrm{LMCut}}$); and PYTRICH is shown with TDG, LMCOUNT, the single model CO4, and LLM (virtual best over all five main models). The selection instance (the smallest benchmark problem per domain) is included in the evaluation set; however, every system solves all six selection instances, so excluding them does not change any comparison.

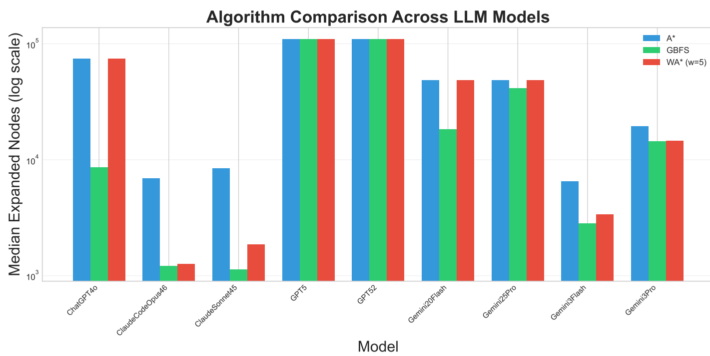
CO4 and LLM solve 131 of 139 problems, compared with 134 for PANDA $\mathrm{RC}^{\mathrm{FF}}$, 118 for LMCOUNT, 117 for TDG, and 113 for PANDA $\mathrm{RC}^{\mathrm{LMCut}}$. CO4 and LLM match or exceed PANDA $\mathrm{RC}^{\mathrm{FF}}$ on five of six domains; Robot is the only exception. Among the PYTRICH baselines, TDG and LMCOUNT both fail to scale to the largest instances: TDG runs out of memory on 22 problems and LMCOUNT on 11 Rover problems, whereas LLM heuristics complete all 139 within the same 8 GB budget. PANDA $\mathrm{RC}^{\mathrm{FF}}$ is the strongest individual baseline, yet LLM matches or exceeds it on five of six domains; the gap narrows to three problems in aggregate, all in the Robot domain where LLM heuristics hit the wall-clock limit on the eight largest instances.



(a) Expanded nodes: LLM virtual best vs. PANDA RC^{FF}.



(b) Cactus plot: problems solved within a given node-expansion budget. LLM reaches its final coverage at lower node counts than PANDA RC^{FF} on all domains except Depots, and arrives at its plateau earlier in four of six domains.



(c) Median expanded nodes (log scale) by search algorithm for each LLM model.

Figure 1: Comparison of LLM and PANDA RC^{FF} on search efficiency and algorithm effects: (a) per-problem expanded nodes (scatter), (b) cumulative coverage versus node-expansion budget (cactus plot), and (c) median expanded nodes by search algorithm for each LLM model. In (a), points below the diagonal indicate an LLM advantage.

5.2 Search Efficiency and Plan Quality

On the 125 problems solved by both the LLM virtual best and PANDA RC^{FF}, the LLM virtual best expands fewer nodes on 104 instances (83%). Figure 1a confirms this visually: nearly all points fall below the diagonal, with Depots as the most competitive domain for PANDA RC^{FF}. The win margin varies by domain: the LLM virtual best wins all 30 Blocksworld problems (26% fewer nodes on average) and all 26 solved Rover problems (74% fewer nodes), and achieves consistent advantages in Towers (33% fewer, 13/13 wins), Robot (27% fewer, 10/11 wins), and Barman (55% fewer, 12/18 wins). Depots is the most balanced domain, where the LLM virtual best wins only 13 of 27 shared problems with a 14% average improvement.

Against PYTRICH TDG, the LLM virtual best wins on every shared instance. The improvement is largest in Barman-BDI (97% fewer nodes) and smallest in Towers (25% fewer nodes), consistent with Towers having the most regular decomposition structure and TDG providing a tight lower bound in that domain. Per-domain average improvements when the LLM virtual best wins: Robot 63%, Depots 61%, Blocksworld-GTOHP 53%, Rover-GTOHP 38%, Towers 25%.

Figure 1b reinforces these per-instance results from a cumulative perspective. LLM solves its first problems at a lower node budget than PANDA RC^{FF} in every domain except Depots, and its coverage curve plateaus at the same level or higher in five of six domains. The steepest early advantage appears

Table 1: Coverage (problems solved) per domain and in aggregate. All systems report the virtual best over GBFS, A*, and WA*. LMCOUNT is PYTRICH with bidirectional landmarks [21]. CO4 is the single heuristic generated by Claude Opus 4. LLM is the virtual best over all five main models.

		PANDA		PYTRICH			
Domain	Probs.	$\mathrm{RC}^{\mathrm{FF}}$	$\mathrm{RC}^{\mathrm{LMCut}}$	TDG	LMCOUNT	CO4	LLM
Barman-BDI	20	18	14	18	19	**20**	**20**
Blocksworld-GTOHP	30	**30**	25	23	**30**	**30**	**30**
Depots	27	**27**	24	23	**27**	**27**	**27**
Robot	20	**20**	**20**	11	11	12	12
Rover-GTOHP	27	26	18	**27**	16	**27**	**27**
Towers	15	13	12	**15**	**15**	**15**	**15**
Total	139	**134**	113	117	118	131	131

in Rover-GTOHP and Barman-BDI. At a budget of 1,000 expanded nodes, LLM has already solved a majority of instances in those domains, while PANDA $\mathrm{RC}^{\mathrm{FF}}$ has solved few or none. In Depots, the two curves interleave throughout, consistent with the per-instance win rate of 13/27. The Towers and Blocksworld curves are identical in shape to those of PANDA $\mathrm{RC}^{\mathrm{FF}}$ but shifted left, confirming that both systems solve the same problems and LLM does so with fewer node expansions.

PYTRICH produces shorter plans than PANDA on every shared problem, with a median improvement of 64% (Appendix E.3). Both systems count only primitive actions in the final plan, and the gap is present under all three search algorithms. Yousefi et al. [25] show that A is incomplete for total-order HTN planning even with the perfect heuristic, because recursive task decompositions create infinite zero-cost cycles. Thus, no HTN planner is guaranteed to find an optimal-length plan, and differences in plan length across planners are expected. We attribute the gap to planner-level differences between PANDA and PYTRICH rather than to the heuristic, as the intersection analysis in Appendix E.3 shows that all PYTRICH heuristics produce plans of almost identical length on the problems solved by all systems.

Within PYTRICH, the plan-quality advantage of LLM over TDG is modest: LLM produces shorter plans on Barman-BDI (18/18 wins, 17% shorter on average), Rover-GTOHP (18/27 wins, 5% shorter), and Blocksworld-GTOHP (5/23 wins, 4% shorter), while all remaining shared instances tie and TDG wins zero problems.

5.3 LLM Model Comparison

The main comparison covers five models: Claude Opus 4, Gemini 2.0 Flash, Gemini 2.5 Pro, Gemini 3 Flash, and Gemini 3 Pro, whose Depots heuristic failed at runtime on every Depots problem. The remaining four models (GPT-4o, Claude Sonnet 4.5, GPT-5, and GPT-5.2) produced working heuristics in only one domain each, so we exclude them from the per-domain tables.

Claude Opus 4 achieves the best search efficiency among all models with a median of 1,878 expanded nodes, beating PANDA $\mathrm{RC}^{\mathrm{FF}}$ (2,178 nodes) and approaching PANDA $\mathrm{RC}^{\mathrm{LMCut}}$ (1,184 nodes). It achieves full coverage on five domains; on Robot, its selected heuristics exceeded the SLURM wall-clock limit on the 8 largest problems and the remaining 12 were all solved. Gemini 3 Flash is the second-best model at 4,346 median nodes; Gemini 3 Pro follows at 14,746 nodes; Gemini 2.0 Flash and Gemini 2.5 Pro are substantially weaker at approximately 48,600 and 51,200 nodes respectively. Model variance is high. The ratio between the best and worst of the five main models is roughly 27$\times$ in median node expansions, indicating that model choice matters more than algorithm choice for heuristic quality.

Across the nine models and six domains, we generated 780 candidate heuristics. Of these, 419 passed the local generate-evaluate-select filter, and we deployed them to the HPC cluster. The remaining 361 were rejected at selection time because they failed to parse, raised an exception on the smallest training instance, or exceeded the selection-step timeout. Of the 419 deployed candidates, 347 were viable (solved at least one benchmark problem) and 72 broke at runtime on every problem. The dominant runtime-failure mode is a state-API misunderstanding. PYTRICH represents states as bitwise integers, but 60 of the 72 broken candidates (83%) were written assuming the state was another structure (e.g., a set). The remaining failures were hallucinations (e.g., LLMs inventing attributes for the node API), missing imports, and typos. These failures persisted despite the prompt explicitly specifying the bitwise-integer state representation and the required `Heuristic` interface.

Four of the nine models (GPT-4o, Claude Sonnet 4.5, GPT-5, and GPT-5.2) produced 20 candidate heuristics for every domain, but in five of six domains *none* of their 20 candidates passed the local selection step. GPT-4o and Claude Sonnet 4.5 retained surviving candidates only on Depots; GPT-5 and GPT-5.2 only on Towers. We did not modify the prompt template to retry these failures, since doing so after observing test results would constitute selection bias against the very benchmark instances used for evaluation. We therefore report this outcome as a negative finding. Domain-specific prompting at the default sampling temperature is not yet reliable enough to produce even one executable heuristic in five of six domains for nearly half of the LLMs we tested.

5.4 Effect of Search Algorithm

Across all LLM runs, GBFS achieves the lowest median expanded nodes (10,553), followed by WA* (14,705) and Standard A* (23,502), with GBFS roughly $2.2\times$ more efficient than A* and $1.4\times$ more efficient than WA* (Figure 1c). The algorithm effect is larger for stronger heuristics: for Claude Opus 4, GBFS (1,220 nodes) and WA* (1,268 nodes) are nearly identical while A* (6,915 nodes) is $5.7\times$ worse than GBFS, whereas for Gemini 3 Flash the ratio is only $2.3\times$ (GBFS 2,836, WA* 3,376, A* 6,504). The plan-length gap between PYTRICH and PANDA holds across all three algorithms, confirming it is not an artefact of the choice of search algorithm.

6 Discussion

LLM Heuristics for HTN vs. Classical Planning The pattern of results differs from the classical-planning case of Corrêa et al. [5], where the LLM virtual best matches or exceeds state-of-the-art baselines across the board. Here, PANDA $\mathrm{RC}^{\mathrm{FF}}$ retains a three-problem advantage in aggregate coverage (134 vs. 131), while the LLM virtual best shows an advantage in search efficiency, expanding fewer nodes than PANDA on 83% of shared instances. The coverage gap lies entirely in the Robot domain, where the selected LLM heuristics time out on the 8 largest problems rather than failing to find a solution. On the 131 problems where an LLM heuristic completed within the budget, the solve rate matches PANDA $\mathrm{RC}^{\mathrm{FF}}$, suggesting the gap reflects search-time scalability rather than inherent planning difficulty. The plan-length gap between PYTRICH and PANDA is consistent in our experiments, but Section 5.2 indicates that it is primarily a planner-level effect. Within PYTRICH, different heuristics produce near-identical plan lengths on the shared problem set.

Why LLM-Generated Heuristics Work in HTN Planning The HDDL domain encoding provided in the prompt gives the LLM explicit access to the decomposition structure of the domain: method names, task hierarchies, and operator preconditions and effects. This semantic richness allows the LLM to reason about which compound tasks are costly and which are cheap, producing estimates that are more informative than the purely syntactic relaxation that TDG computes. In domains with pronounced hierarchical structure, the gains over TDG are largest: the LLM virtual best expands 97% fewer nodes in Barman-BDI and 38% fewer in Rover-GTOHP, suggesting that the generated heuristics exploit method-level knowledge. Towers is the domain where TDG competes most closely with LLM heuristics (25% fewer nodes for the LLM virtual best). The Tower-of-Hanoi decomposition is highly regular and predictable, so the TDG estimate is a tight lower bound in this domain and leaves little room for additional semantic guidance. This contrast between Barman and Towers provides evidence that LLM heuristics add value in proportion to the semantic complexity of the decomposition hierarchy.

Model and Algorithm Effects The $27\times$ spread in median expanded nodes across the five main models is the most striking model-level finding. Newer models are not uniformly better. The generate-evaluate-select procedure partially compensates for weak models: even Gemini 2.0 Flash and Gemini 2.5 Pro contribute to full coverage on the domains where their selected heuristics run without error. The efficiency gain from switching to GBFS scales with heuristic quality: Claude Opus 4 gains $5.7\times$ (6,915 vs. 1,220 median nodes) while Gemini 3 Flash gains only $2.3\times$. This interaction suggests that discarding g-values is most beneficial when the heuristic itself encodes decomposition cost, since in that regime tracking path cost adds noise rather than signal.

7 Related Work

HTN heuristics. HTN planning encodes domain knowledge in the decomposition hierarchy itself, complementing rather than replacing search heuristics [6, 7]. A line of work develops increasingly informative HTN heuristics, from TDG-relaxation estimates [3, 15] to landmark counting [11, 21]; PANDA [2, 3] aggregates these into the strongest available reachability-based system. The 2020 IPC HTN winner, HYPERTENSION [18], achieved top coverage with no admissible heuristic at all, motivating our investigation of whether LLM-generated heuristics can close this gap.

LLMs as planners. LLMs perform poorly as planners [23]; reliable use requires coupling them with sound search [22, 5]. In the HTN setting, Xu and Munoz-Avila [24] use LLMs to propose decompositions online and Muñoz-Avila et al. [19] interleave LLM-generated and symbolic decomposition; Oswald et al. [20] use them to author PDDL domains. We use LLMs only to write the heuristic and delegate correctness to the search algorithm.

Learned heuristics for symbolic planning. Tuisov et al. [22] argue that domain-independence may no longer be the right yardstick once LLMs can synthesise per-domain heuristics on demand. Building on this, Corrêa et al. [5] prompt LLMs to write Python heuristics for classical planning, outperforming domain-independent baselines. We adapt their pipeline to HTN planning, where the heuristic must reason over task networks and decomposition methods rather than flat states.

8 Conclusion

We investigate whether LLM-generated heuristics can serve as effective search guidance for HTN planning, extending the methodology of Corrêa et al. [5] from classical to hierarchical planning. The answer is affirmative: CO4, selected automatically on a single training instance, solves 131 of 139 benchmark problems and reduces node expansions on 83% of shared instances against PANDA $\mathrm{RC}^{\mathrm{FF}}$.

HTN planning encodes domain knowledge directly in the task hierarchy, providing search guidance through decomposition choices rather than explicit heuristics [6]. This design has been effective enough that the 2020 IPC HTN winner, HYPERTENSION, achieved top coverage with no admissible heuristic [18]. Prior work has focused on acquiring methods automatically from classical operators [17], noisy observations [8], or curriculum learning [16], reducing the manual effort of encoding that hierarchy. Our work takes a complementary path: given an existing HDDL encoding, we acquire a heuristic that exploits the hierarchy rather than the hierarchy itself. Tuisov et al. [22] ask whether domain-independence remains a meaningful goal in the era of LLMs; our results sharpen this question in the HTN setting, where the task hierarchy already encodes domain knowledge and the LLM heuristic functions as a second layer of domain-specific guidance that exploits that encoding directly.

The main limitation of the current study is scope: our evaluation covers six total-order HTN domains and does not address partial-order planning, numerical fluents, or temporal domains. The offline heuristic-generation cost (up to 20 candidate evaluations per model-domain pair) is negligible when amortised over many problems but may be prohibitive for single-problem or rapidly changing deployments.

Extending the approach to partial-order HTN planning is the most important open direction, as the heuristic must then reason about the combinatorial ordering space of the task network rather than a fixed linear sequence. A domain-independent prompting condition, without the HDDL file or hint blocks, would determine how much of the observed gain derives from explicit domain knowledge supplied in the prompt versus the LLM's general reasoning about planning structure.

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Use unnumbered first level headings for the acknowledgments. All acknowledgments go at the end of the paper before the list of references. Moreover, you are required to declare funding (financial activities supporting the submitted work) and competing interests (related financial activities outside the submitted work). More information about this disclosure can be found at: https://neurips.cc/Conferences/2026/PaperInformation/FundingDisclosure.

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A Prompt Templates

A.1 Base Prompt Structure

The base prompt is a structured document with twelve sections delivered to the LLM for each domain. Sections 1–3 supply domain-specific information; sections 4–12 are fixed across all domains.

1. **Task preamble.** States the role (*expert in hierarchical planning and heuristic design*), the target domain, and the required class name and parameter name for the generated Python class.
2. **Domain definition.** The full HDDL domain file, presented verbatim in a fenced code block.
3. **Training instances.** Two benchmark problems: the smallest (used for heuristic selection) and the largest available, both presented verbatim in HDDL format.
4. **Domain-specific hints.** Present only when a hint block exists for the domain (see Appendix B). Introduced with the instruction *"These insights were discovered through extensive experimentation on this domain. Use them."*

Sections 5–12 are identical across all domains and prompts.

Section 5 — Grounded fact format. Explains that after grounding, facts are represented as `+predicate[arg1,arg2]` rather than in HDDL syntax, and provides a reference implementation of a parser:

Listing 1: Reference fact-name parser included verbatim in the prompt.

```
def _parse_fact_name(self, name: str):
    name = name.strip()
    if name.startswith("+") or name.startswith("-"):
        name = name[1:]
        bracket_idx = name.find("[")
        if bracket_idx > 0 and name.endswith("]"):
            predicate = name[:bracket_idx]
            args_str = name[bracket_idx+1:-1]
            args = args_str.split(",") if args_str else []
            return predicate, args
    return None, []
```

Section 6 — Goal state access. Explains that `model.goals` is a bitwise integer, not a list of predicates, and shows the correct API call to retrieve goal fact names:

```
goal_fact_names = self.model.state_explicit_repr(self.model.goals)
# Returns: ['+communicated_soil_data[waypoint1]', ...]
```

Section 7 — Bitwise state checks. Contrasts the correct O(1) method against the incorrect string-based alternative:

```
# CORRECT: O(1) bitwise check
is_true = (state_bitwise >> fact.global_id) & 1

# WRONG: O(n) string scan that causes timeouts on large instances
fact.name in self.model.state_explicit_repr(state)
```

Section 8 — Required imports and method signatures. States the mandatory import paths and provides correct and incorrect variants of the two required method signatures:

```
from Pytrich.Heuristics.heuristic import Heuristic
from Pytrich.Search.htn_node import HTNNode
from Pytrich.model import Model
```

```
def initialize(self, model: Model, initial_node: HTNNode):
    h_value = self._compute(initial_node.state, initial_node.task_network)
    return super().initialize(model, h_value)

def __call__(self, parent_node: HTNNode, node: HTNNode) -> int:
    h_value = self._compute(node.state, node.task_network)
    super().update_info(h_value)
    return h_value
```

Section 9 — Working example heuristic. A complete, working heuristic for the domain is provided verbatim. It demonstrates correct fact parsing, bitwise state access, preprocessing in `initialize`, and O(1) evaluation in `__call__`.

Section 10 — Class definitions. Full Python class definitions for `Fact`, `Operator`, `AbstractTask`, `Decomposition`, and `Model` are given verbatim so the LLM knows every attribute and method available at runtime.

Section 11 — Admissibility vs. guidance. Explains that admissible lower bounds and tie-breaking penalties compose additively, and that sub-unit tie-breaking magnitudes (e.g. $\times 0.001$) preserve admissibility while breaking symmetries.

Section 12 — Winning and losing patterns. Six winning patterns (P1–P6) and four anti-patterns (A1–A4) are listed, each with a short code example. The patterns were distilled from the failure analysis described in Section 5.3 and reflect the dominant failure modes observed across the nine models.

Section 13 — Required design procedure. The LLM is instructed to follow five steps and write the justification as top-of-file comments in the generated code: (1) name the domain bottleneck; (2) list two to three independent admissible lower bounds; (3) implement `initialize`; (4) implement `__call__` returning `max(term1, term2, ...)`; (5) add tie-breaking penalties if the domain has interchangeable parameters. The LLM is asked to return a structured response (filename and code) to enable automated parsing.

A.2 Iterative Refinement Prompt

The refinement prompt appends a feedback section to the base prompt. The section includes: the previous candidate code verbatim; a results table comparing the candidate against the TDG baseline on the selection instance (expanded nodes, wall time, solution size, exit status); and auto-generated corrective guidance keyed to the observed failure mode.

Guidance is generated by inspecting the previous code for structural signatures:

- **TIMEOUT**: If the code iterates `self.model.facts` or `self.model.operators` inside `__call__`, the feedback explicitly names this as anti-pattern A3 and instructs the LLM to move that work to `initialize`.
- **Worse than TDG**: If the code never reads state bits (no >> or `& 1` patterns), the feedback flags anti-pattern A1 and recommends adding state-aware per-task cost estimation. If no `max(` composition is present, the feedback recommends adding a second admissible lower bound.
- **Better than TDG**: The feedback acknowledges the improvement and suggests tightening an existing term or adding a third `max` component.
- **Runtime error**: The error message is shown verbatim and the LLM is instructed to fix it.

The instruction *"Do NOT start from scratch — modify and improve the previous version"* is highlighted to prevent the LLM from discarding working structure when only a single component needs improvement.

B Details on Hints

We provide per-domain hint blocks to reduce recurrent prompt and interface errors when generating HTN heuristics. Each block contains three categories of guidance.

(1) Representation caveats. These hints document grounding-specific behavior that frequently causes implementation failures. In our setup, the PANDA grounder strips static facts from the grounded domain at compilation time, so information such as object-location bindings or traversal constraints must often be recovered from grounded operator arguments rather than directly from state fluents. The grounder also compiles method preconditions into dedicated precondition-check operators, so prompts instruct models to inspect relevant operators when deriving decomposition-aware estimates.

(2) Dominant search bottleneck. These hints identify the primary source of branching in each domain. Examples include shot-choice symmetry in Barman, the single-carry constraint in Robot, and repeated shortest-path computation in Rover. The block explicitly recommends moving expensive graph or table construction to preprocessing so per-node heuristic evaluation remains lightweight.

(3) Heuristic-construction guidance. These hints suggest candidate lower-bound components, symmetry-breaking signals, and effective penalty scales. We include magnitude guidance because many generated heuristics produce logically correct tie-breaking terms that are too small to influence queue ordering.

Relation to checklist-style prompting. Our design is inspired by the checklist-style guidance used in prior work on LLM-generated classical planning heuristics [5]. As in that line of work, guidance is refined iteratively from observed failures. In our pipeline, the refinement step is LLM-assisted: after each round, we provide run outcomes and request a concise summary of dominant failure modes and a revised hint block. The experimenter triggers this loop and accepts the revised text, but does not write heuristic code.

C Experimental Details

C.1 Models Used

Table 2 lists all evaluated models.

Table 2: LLM models evaluated. †Selected heuristic failed at runtime on all problems in every domain except Depots. ‡Selected heuristic failed at runtime on all problems in every domain except Towers. §Selected heuristic failed at runtime on all Depots problems.

Key in results	Model name	Provider
ClaudeCodeOpus46	Claude Opus 4	Anthropic
ClaudeSonnet45†	Claude Sonnet 4.5	Anthropic
Gemini20Flash	Gemini 2.0 Flash	Google
Gemini25Pro	Gemini 2.5 Pro	Google
Gemini3Flash	Gemini 3 Flash	Google
Gemini3Pro§	Gemini 3 Pro	Google
GPT4o†	GPT-4o	OpenAI
GPT5‡	GPT-5	OpenAI
GPT52‡	GPT-5.2	OpenAI

C.2 Generation settings

For candidate generation, we use provider-default sampling settings and cap responses at 16,384 tokens. Each model-domain pair generates 20 one-shot candidates, evaluated and selected as described in Section 3.3.

C.3 Execution details

All jobs are executed through SLURM job arrays with one benchmark instance per task. Each task is allocated 1 CPU core, 8 GB RAM, and a 30-minute wall-clock limit. Both PYTRICH and PANDA runs use the same resource limits.

C.4 Model-specific failures

Four models (GPT-4o, Claude Sonnet 4.5, GPT-5, GPT-5.2) produced selected heuristics that were executable in only one domain each. Gemini 3 Pro produced executable heuristics in five domains but failed on all Depots instances. These outcomes are included in the aggregate accounting and discussed in Section 5.3.

D Generated Heuristic Examples

This appendix presents two heuristics generated for the Rover-GTOHP domain to illustrate the quality gap between the best and weakest models. The Rover domain is chosen because it shows the largest average node-expansion improvement (74% fewer nodes than PANDA $\mathrm{RC}^{\mathrm{FF}}$) and exhibits the clearest contrast in heuristic design quality.

D.1 Strong Heuristic: Claude Opus 4 on Rover-GTOHP

The following heuristic was generated by Claude Opus 4 and selected as the best of 20 candidates for this domain. It combines two complementary estimates: a task-network cost based on a fixed-point minimum-decomposition computation (similar in spirit to TDG but computed locally per call using prebuilt cost tables), and a state-aware goal-pipeline distance that tracks which stages of the soil, rock, and image data collection pipeline each goal has already completed. The two estimates are summed rather than maximised because they measure different unavoidable costs that do not overlap. Heavy preprocessing (cost-table fixed point, fact categorisation) runs once in `initialize`.

Listing 2: Best selected heuristic for Rover-GTOHP (Claude Opus 4). Abridged: `_preprocess_facts`, `_preprocess_tasks`, `_task_network_cost`, `_parse_name`, `_any_true`, `_any_calibrated`, and `_rover_at_waypoint` helpers omitted.

```
class RoverGoalDistanceHeuristic(Heuristic):

    def initialize(self, model: Model, initial_node: HTNNode):
        self._preprocess_facts()    # categorise facts by predicate
        self._preprocess_tasks()    # parse abstract-task names
        self._compute_min_costs()   # fixed-point TDG-like table
        h_value = self._compute(initial_node.state, initial_node.task_network)
        return super().initialize(model, h_value)

    def _compute_min_costs(self):
        """Fixed-point: min decomposition cost for each task."""
        for op in self.model.operators:
            self.task_min_cost[op.global_id] = 1
        for at in self.model.abstract_tasks:
            self.task_min_cost[at.global_id] = 100
        changed = True
        while changed:
            changed = False
            for at in self.model.abstract_tasks:
                best = min(
                    sum(self.task_min_cost.get(t.global_id, 1)
                        for t in d.task_network)
                    for d in at.decompositions
                )
                if best < self.task_min_cost[at.global_id]:
                    self.task_min_cost[at.global_id] = best
                    changed = True

    def _goal_distance(self, state):
        """State-aware pipeline cost for each unsatisfied goal."""
        h = 0
        n_samples = 0
        for fact, wp in self.soil_goals:
            if (state >> fact.global_id) & 1:
                continue
```

```
            analysis = self.soil_analysis_by_wp.get(wp)
            if analysis and self._any_true(state, analysis):
                h += 4   # navigate + communicate
            else:
                h += 10  # full pipeline: navigate + empty store + sample + send
                n_samples += 1
        for fact, wp in self.rock_goals:
            if (state >> fact.global_id) & 1:
                continue
            analysis = self.rock_analysis_by_wp.get(wp)
            h += 4 if (analysis and self._any_true(state, analysis)) else 10
            if h == 10: n_samples += 1
        for fact, obj, mode in self.image_goals:
            if (state >> fact.global_id) & 1:
                continue
            images = self.image_by_obj_mode.get((obj, mode))
            if images and self._any_true(state, images):
                h += 4
            else:
                h += 9 if self._any_calibrated(state) else 12
        if n_samples > 1:
            h += (n_samples - 1) * 3   # store-drop penalty between samples
        return h

    def _compute(self, state, task_network):
        return (self._task_network_cost(state, task_network)
                + self._goal_distance(state))

    def __call__(self, parent_node: HTNNode, node: HTNNode) -> int:
        h_value = self._compute(node.state, node.task_network)
        super().update_info(h_value)
        return h_value
```

D.2 Weak Heuristic: Gemini 2.5 Pro on Rover-GTOHP

The following heuristic was generated by Gemini 2.5 Pro. It exemplifies anti-patterns A1 and A4 from the prompt guidelines: it ignores the world state entirely, assigns fractional penalties (≤ 0.5) to each method rather than computing realistic task costs, and reads the method that generated the current node rather than the remaining task network. Because the heuristic value responds only to which decomposition was most recently applied and not to how much work remains, it provides no useful guidance once the search moves more than one step from the root.

Listing 3: Weak heuristic for Rover-GTOHP (Gemini 2.5 Pro).

```
class RoverGemini25ProHeuristic0(Heuristic):

    def __init__(self, ...):
        self.penalties = {
            'navigation': 0.5, 'data_collection': 0.3,
            'calibration': 0.2, 'communication': 0.15,
            'resource_management': 0.1, 'nop': 0.0
        }
        self.method_scores = {}

    def initialize(self, model, initial_node):
        self.model = model
        self._precompute_method_info()
        h_value = self._calculate_node_heuristic(initial_node)
        return super().initialize(model, h_value)

    def _precompute_method_info(self):
        """Assigns a weighted sum of sub-task penalties to each method."""
        for method in self.model.decompositions:
            score = 0.0
            for subtask in method.task_network:
                name = subtask.name.lower()
                if 'navigate' in name:    score += 0.5
                elif 'sample' in name:    score += 0.3
                elif 'calibrate' in name: score += 0.2
                elif 'send' in name:      score += 0.15
                elif 'empty' in name:     score += 0.1
            self.method_scores[method.name] = score

    def _calculate_node_heuristic(self, node):
        # Reads the method that produced this node, not the remaining network
        if not hasattr(node, 'method') or not node.method:
```

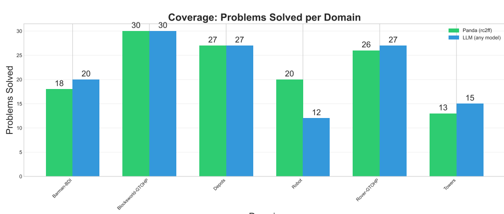
```
            return 0.0
        return self.method_scores.get(node.method.name, 1.0)

    def __call__(self, parent_node, node):
        h_value = self._calculate_node_heuristic(node)
        super().update_info(h_value)
        return h_value
```

The contrast between Listings 2 and 3 illustrates the key design dimensions that separate strong from weak LLM-generated heuristics: state-awareness (bit tests vs. none), cost realism (pipeline-calibrated constants vs. fractional penalties), and network-awareness (remaining tasks vs. last applied method).

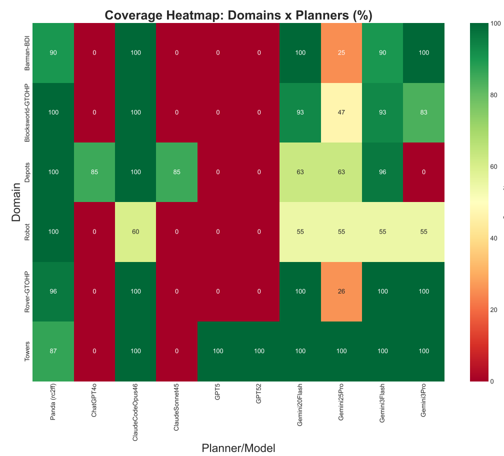
E Additional Results and Figures

This appendix contains the complete set of comparison figures for all three baselines. The main paper includes scatter plots and the algorithm-comparison chart for PANDA RC^{FF}; all remaining figures appear here. All figures use the LLM virtual best over the five main models and three search algorithms.

E.1 PANDA RC^{FF} (Primary Baseline)



(a) Coverage by domain. LLM matches or exceeds PANDA RC^{FF} on five of six domains; Robot is the exception due to wall-clock timeouts on the eight largest instances.



(b) Coverage heatmap across models and domains. Claude Opus 4 achieves full coverage on five domains; Gemini 2.5 Pro and GPT-5 variants each solve only one domain.

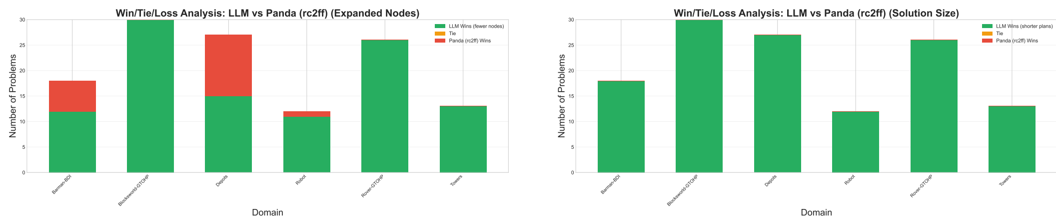
Figure 2: Coverage results for LLM vs. PANDA RC^{FF}: per-domain bar chart (a) and per-model heatmap (b).

E.2 PANDA RC^{LMCut}

This subsection mirrors the RC^{FF} comparison for completeness. Since PANDA RC^{LMCut} solves fewer problems than PANDA RC^{FF}, the shared instance set is smaller in several domains.

E.3 Plan Length by Domain

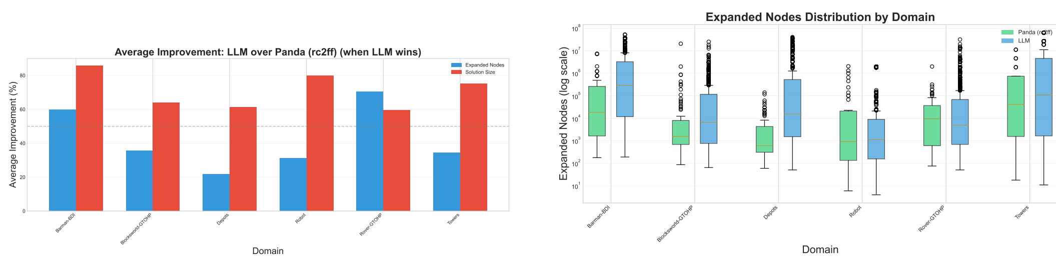
Table 3 reports median plan length restricted to the problems solved by all six systems, with each entry being the virtual best over the three search algorithms. All four PYTRICH-based systems (TDG, LMCOUNT, CO4, and LLM) produce identical median plan length in four of six domains and differ by at most five actions in the remaining two (Barman-BDI and Robot), confirming that heuristic choice has little effect on plan quality within PYTRICH. The gap between PANDA and PYTRICH is large and consistent: on the shared problem set, PANDA produces plans roughly 3× longer than any PYTRICH heuristic. Yousefi et al. [25] establish that A is incomplete for total-order HTN planning,



(a) Win/loss on expanded nodes. LLM wins on 104 of 125 shared instances; Depots is the only domain where PANDA RC^{FF} wins more than a handful of instances.

(b) Win/loss on solution size. LLM produces shorter plans on all 125 shared instances; the bar shows 125 wins and zero losses across all six domains.

Figure 3: Win/loss breakdown by domain: LLM vs. PANDA RC^{FF} on expanded nodes (a) and solution size (b). Each bar segment counts shared instances where LLM expands fewer (win), equal (tie), or more (loss) nodes or actions.



(a) Average percentage improvement in expanded nodes on instances where LLM wins. Rover-GTOHP shows the largest improvement (74%); Depots the smallest (14%).

(b) Boxplot of expanded nodes per domain, restricted to problems solved by both systems. Rover-GTOHP and Blocksworld-GTOHP show the tightest LLM advantage; Depots shows the widest spread.

Figure 4: Search efficiency detail: LLM vs. PANDA RC^{FF}. Panel (a) shows mean improvement on LLM wins; panel (b) shows the full distribution of node counts per domain.

so differences in plan length across planners with different internal search strategies are unsurprising (see also Section 5.2).

E.4 Median Expanded Nodes by Model and Algorithm

Table 4 reports median expanded nodes broken down by model, algorithm, and domain. Dashes indicate that the model produced no working heuristics for that domain. CO4 rows are highlighted in bold; the overall median pools all problems solved by each model under each algorithm.

E.5 PYTRICH-TDG

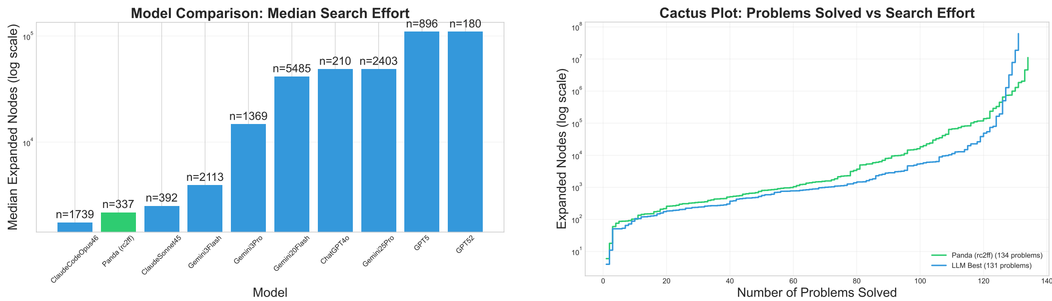
This subsection compares LLM against PYTRICH guided by TDG. The figures report the same metrics as above: coverage, expanded nodes, and plan length on shared solved instances.

F Heuristic API Details

This appendix describes the implementation-level interface used for all LLM-generated heuristics.

Heuristic class. Each heuristic subclasses `Heuristic` and implements two methods:

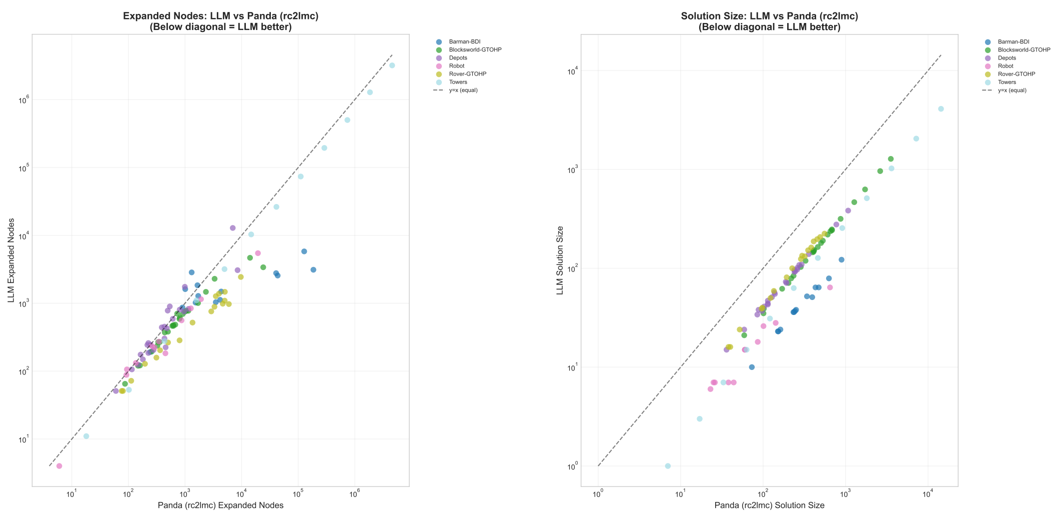
- `initialize(self, model: Model, initial_node: HTNNode)`: called once before search for preprocessing.
- `__call__(self, parent_node: HTNNode, node: HTNNode) -> int`: called at each node expansion; returns a non-negative integer estimate of remaining solution cost.



(a) Median expanded nodes per model on problems each model solved. Claude Opus 4 is the only LLM model that beats PANDA $\mathrm{RC}^{\mathrm{FF}}$ in median search effort; models with results in only one domain are shown with a dagger.

(b) Cactus plot: problems solved within a given node-expansion budget. LLM reaches its final coverage at lower node counts than PANDA $\mathrm{RC}^{\mathrm{FF}}$ on all domains except Depots.

Figure 5: Model ranking and cumulative coverage: LLM vs. PANDA $\mathrm{RC}^{\mathrm{FF}}$. Panel (a) compares median search effort per LLM model against the two PANDA variants; panel (b) shows how coverage accumulates as the node budget grows.



(a) Expanded nodes: LLM vs. PANDA $\mathrm{RC}^{\mathrm{LMCut}}$. PANDA $\mathrm{RC}^{\mathrm{LMCut}}$ achieves the lowest median node count of all baselines (1,184), but LLM wins on the majority of shared instances in Barman, Blocksworld, Rover, and Towers.

(b) Solution size: LLM vs. PANDA $\mathrm{RC}^{\mathrm{LMCut}}$. LLM produces shorter plans on all shared instances. Rover and Towers are absent because PANDA $\mathrm{RC}^{\mathrm{LMCut}}$ does not solve them.

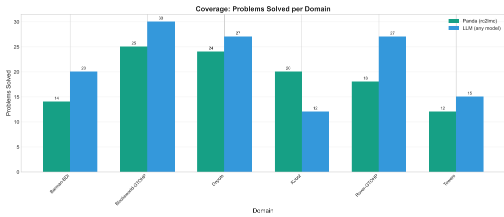
Figure 6: Per-problem scatter plots: LLM vs. PANDA $\mathrm{RC}^{\mathrm{LMCut}}$ on expanded nodes (a) and solution size (b). Points below the diagonal indicate LLM advantage.

Model interface. The `Model` object exposes grounded planning objects including `facts`, `operators`, `abstract_tasks`, `decompositions`, and the goal bitset `goals`.

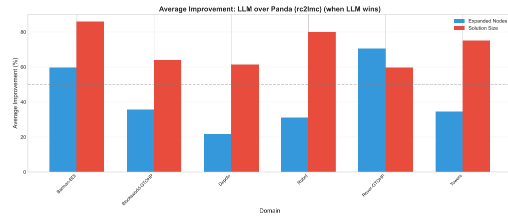
Node interface. Each `HTNNode` provides:

- `node.state`: integer bitset encoding the current state;
- `node.task_network`: ordered remaining tasks (each tagged primitive or abstract);
- `node.method`: the decomposition method that produced this node, or `None` at the root.

Bitset access. Fact truth checks use constant-time bit operations, `(node.state >> fact.global_id) & 1`, and operator preconditions/effects are also represented as bitsets. This allows efficient reachability-style computations without string parsing.



(a) Coverage by domain. PANDA RC$^{\text{LMCut}}$ solves only 113 of 139 problems overall, failing to achieve full coverage on Rover-GTOHP (18/27) and Towers (12/15), where LLM achieves full coverage.



(b) Average percentage improvement in expanded nodes on instances where LLM wins. The pattern differs from the RC$^{\text{FF}}$ comparison: Depots shows a larger advantage because RC$^{\text{LMCut}}$ performs poorly on Depots relative to RC$^{\text{FF}}$.

Figure 7: Coverage and search-efficiency summary: LLM vs. PANDA RC$^{\text{LMCut}}$.

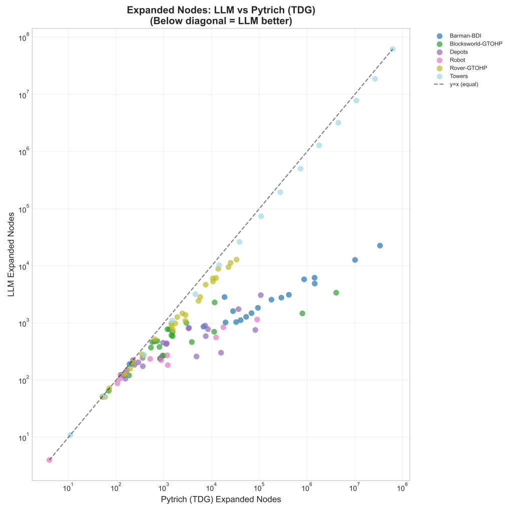
Table 3: Median plan length (primitive actions) per domain, restricted to the problems solved by all six systems. Each entry is the virtual best over the three search algorithms (GBFS, A*, WA*).

		PANDA		PYTRICH			
Domain	n	RC$^{\text{FF}}$	RC$^{\text{LMCut}}$	TDG	LMCOUNT	CO4	LLM
Barman-BDI	14	248	248	43	39	38	38
Blocksworld-GTOHP	23	410	410	150	150	150	150
Depots	23	139	139	57	57	57	57
Robot	11	44	44	7	7	11	7
Rover-GTOHP	16	217	209	92	90	92	90
Towers	12	348	348	95	95	95	95
Median		232	228	74	74	74	74

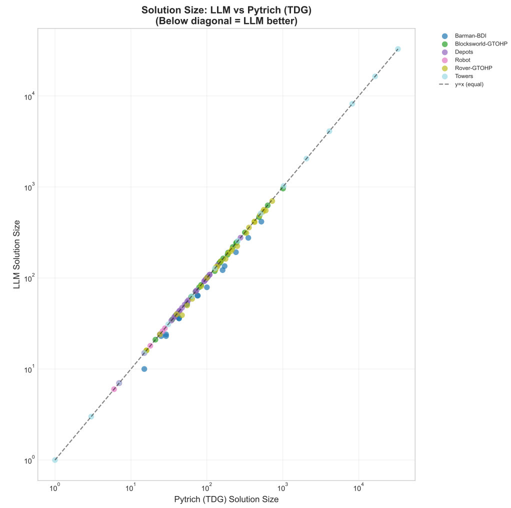
Grounded fact naming. Grounded facts follow runtime names such as `+predicate[arg1,arg2]` and `-predicate[arg1,arg2]`, which differ from raw HDDL syntax. Prompts include this convention explicitly to avoid generation errors.

Table 4: Median expanded nodes by model, algorithm, and domain. LLM pools all LLM models; baselines use their default algorithm.

Model	Algo	Barman	Blocks.	Depots	Robot	Rover	Towers	Overall
LLM	GBFS	197,098	2,925	8,614	1,011	4,783	110,335	10,553
LLM	WA*	286,594	3,726	21,602	1,086	2,952	110,639	14,705
LLM	A*	377,048	25,352	23,502	1,150	6,318	110,468	23,502
GPT-4o	GBFS	—	—	8,614	—	—	—	8,614
	WA*	—	—	74,097	—	—	—	74,097
	A*	—	—	74,097	—	—	—	74,097
CO4	**GBFS**	**91,328**	**774**	**724**	**351**	**1,657**	**73,632**	**1,220**
	WA*	**74,956**	**777**	**797**	**347**	**1,626**	**73,736**	**1,268**
	A*	**76,928**	**29,526**	**4,754**	**472**	**3,262**	**111,058**	**6,915**
Claude Sonnet 4.5	GBFS	—	—	1,128	—	—	—	1,128
	WA*	—	—	1,860	—	—	—	1,860
	A*	—	—	8,436	—	—	—	8,436
GPT-5	GBFS	—	—	—	—	—	109,274	109,274
	WA*	—	—	—	—	—	109,378	109,378
	A*	—	—	—	—	—	109,484	109,484
GPT-5.2	GBFS	—	—	—	—	—	109,274	109,274
	WA*	—	—	—	—	—	109,378	109,378
	A*	—	—	—	—	—	109,484	109,484
Gemini 2.0 Flash	GBFS	1,193,860	28,504	18,379	1,296	80,128	111,058	18,379
	WA*	3,244,057	64,696	74,097	1,495	71,108	111,162	48,631
	A*	3,244,057	66,868	74,097	1,495	71,108	111,162	48,631
Gemini 2.5 Pro	GBFS	3,376,203	62,760	18,379	1,296	80,128	111,058	41,344
	WA*	3,244,057	69,069	74,097	1,495	71,108	111,162	48,631
	A*	3,244,057	69,069	74,097	1,495	71,108	111,162	48,631
Gemini 3 Flash	GBFS	80,200	1,144	1,102	745	2,812	106,154	2,836
	WA*	71,556	1,210	1,113	736	2,887	105,722	3,376
	A*	110,384	2,601	4,464	756	6,660	108,112	6,504
Gemini 3 Pro	GBFS	10,558	1,200	—	877	1,956	110,459	14,472
	WA*	12,714	1,258	—	884	2,098	110,745	14,573
	A*	15,784	3,914	—	957	3,895	110,444	19,377
Panda RC$^{\text{FF}}$	GBFS	2,074	1,050	449	1,791	8,031	41,069	1,516
	WA*	138,903	1,146	544	707	10,952	41,195	1,574
	A*	327,784	3,213	8,437	986	7,073	41,237	7,790
Panda RC$^{\text{LMCut}}$	GBFS	2,604	673	433	1,589	2,132	27,948	899
	WA*	104,219	677	812	725	1,936	27,986	940
	A*	223,817	2,294	8,472	985	7,731	28,044	4,168
Novelty	GBFS	647,479	45,299	11,890	1,221	15,786	76,243	24,721
TDG	GBFS	84,196	1,278	3,297	891	2,812	109,972	4,449

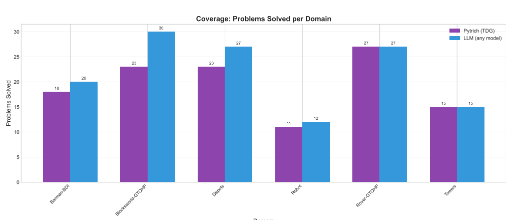


(a) Expanded nodes: LLM vs. TDG. Nearly all points fall well below the diagonal; TDG wins zero instances across all six domains. The 22 large instances missing from TDG due to out-of-memory failures at the 8 GB limit are absent from this plot.

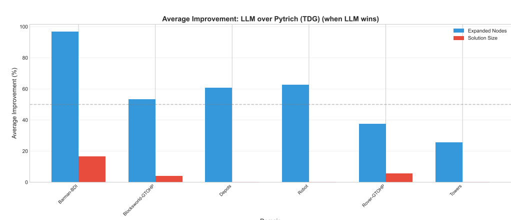


(b) Solution size: LLM vs. TDG. Most points lie on the diagonal, reflecting the structural property that total-order HTN decompositions largely fix plan length regardless of which heuristic guides search. LLM wins on Barman and subsets of Rover and Blocksworld.

Figure 8: Per-problem scatter plots: LLM vs. TDG on expanded nodes (a) and solution size (b). Points below the diagonal indicate LLM advantage.



(a) Coverage by domain. LLM covers 131 problems; TDG covers only 117, missing the 22 largest instances that exceed the 8 GB memory budget. On the 117 instances TDG solves, LLM also solves all of them.



(b) Average percentage improvement in expanded nodes on shared instances where LLM wins. Barman-BDI shows the largest improvement (97%), consistent with TDG providing a loose bound on the shot-choice bottleneck. Towers shows the smallest improvement (25%), where TDG's decomposition-graph bound is relatively tight.

Figure 9: Coverage and search-efficiency summary: LLM vs. TDG.

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    Question: Does the paper describe the usage of LLMs if it is an important, original, or non-standard component of the core methods in this research? Note that if the LLM is used only for writing, editing, or formatting purposes and does *not* impact the core methodology, scientific rigor, or originality of the research, declaration is not required.

    Answer: [Yes]

    Justification: LLMs are the core method of this work. Section 3 describes how LLMs are prompted to generate Python heuristic functions, and Section 4 lists all nine models evaluated, their providers, and generation settings.

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