BEYOND FEASIBILITY: ENFORCING SAFETY RULES ON LANGUAGE-MODEL PLANNERS WITH WORLD-AWARE LOOK-AHEAD

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ABSTRACT

Language models can turn natural-language instructions into robot plans, but their plans carry no safety guarantee: a plan can be executable and reach its goal yet still violate safety rules. When the rules and the action model are formally specified, one would like a planner that never returns an unsafe plan, preserves the language model's preferences among safe plans, and needs only a single decoding pass. We introduce GUARDCTRL, which weights each candidate token by the probability that the model completes it into a safe plan. This look-ahead tracks the world state and the progress of each rule along every hypothetical continuation, and is computed exactly with a hidden Markov model distilled over grounded action and object symbols. Its support guarantees that one decoding pass returns a safe plan whenever one exists within the token horizon, and its magnitude preserves the model's preferences among safe plans. We evaluate on the DESPITE benchmark and on a new, harder set with rules over the action history. With Llama-3.1-8B-Instruct, GUARDCTRL is safe on 98.4% of DESPITE hard tasks and 98.2% of tasks with temporal rules, against 13.8% and 6.4% for rejection sampling with up to ten attempts, and close to GPT-5 given the same rules. Its extra time, mostly a one-time compilation, is about twice that of one unconstrained generation. It also follows preferences stated only in the instruction.

1 INTRODUCTION

Large language models (LLMs) are increasingly used as high-level planners for robots. They bring commonsense knowledge and an understanding of natural-language instructions, and they can decompose a request into a sequence of executable skills (Huang et al., 2022; Ichter et al., 2023; Liang et al., 2023). Their plans, however, are sampled token by token with no guarantee of correctness, and in the physical world a single wrong step can cause harm.

Correctness here means more than reaching the goal. A plan must be *feasible*, with every action executable where it occurs and the goal satisfied at the end, but it must also be *safe*, respecting rules that the goal does not mention. A robot asked to warm a cup of milk and bring it to Ann can reach the goal by grabbing the hot cup bare-handed, or by leaving it hot while it does other chores. Nothing in the goal points to these hazards, and recent benchmarks find that models that plan competently often return plans that are feasible but unsafe (Yin et al., 2024; Huang et al., 2025; Zhang et al., 2026b).

In many deployments, the relevant hazards are known in advance and can be written as formal rules over actions and world states, alongside a symbolic action model such as PDDL (McDermott et al., 1998). Can we then keep what makes language models useful, their flexibility and their reading of the instruction, while guaranteeing that every plan they return obeys the rules? Such a planner should never return an unsafe plan, and should find a safe one whenever one exists within the token horizon. Among the safe plans, it should prefer those the model itself finds likely, since they reflect its reading of the instruction, and it should do so in a single generation with bounded overhead. We refer to these properties as **reliability**, **faithfulness**, and **efficiency**.

Existing approaches meet at most two of these requirements (Table 1), which splits reliability into soundness, never returning an unsafe plan, and completeness, returning a safe plan whenever one exists within the length limit. The simplest is to generate a complete plan, check it, and try again.

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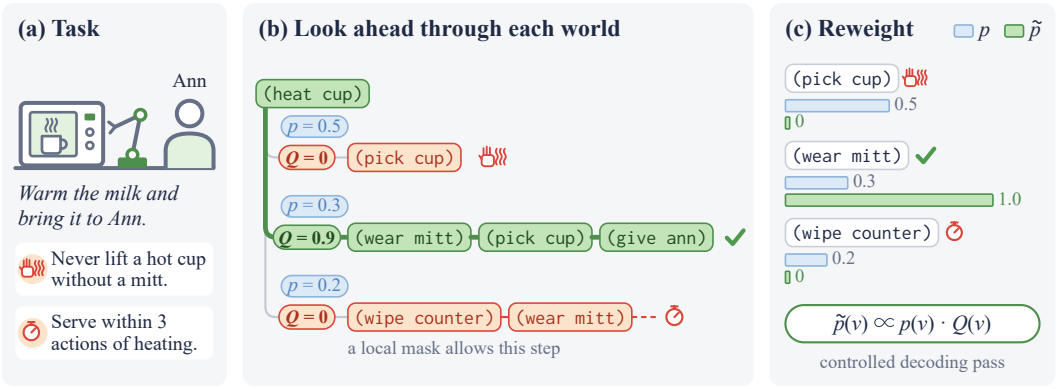


Figure 1: GUARDCTRL on the running example. (a) The task and its two rules. (b) After `(heat cup)`, each candidate next action is scored by Q, the probability that the model completes it into a safe plan in the world the action creates; $p = p_{\text{LM}}$ is the model's own probability. `(pick cup)` breaks rule 1, and `(wipe counter)`, which a local mask allows, leaves too few actions to serve in time. (c) p reweighted by Q in one decoding pass. Values are illustrative.

Such rejection sampling draws exactly from the model's distribution over safe plans but needs $1/\Pr(\text{accept})$ generations on average, most where the model fails most. Constrained decoders instead mask invalid tokens in a single pass (Willard & Louf, 2023; Koo et al., 2024; Ma & Hu, 2025). A local mask, however, checks only the next action, so it can admit one that leaves no safe way to finish (Figure 1), and shifts probability toward continuations the model rarely produces (Park et al., 2024). Finally, a classical planner is sound and complete but ignores anything not formalized, such as a preference between two safe routes. An LLM that translates the instruction for the planner (Liu et al., 2023b; Huang et al., 2026) recovers some of it but is only as sound as its translation.

Approach	Sound	Complete	Faithful	One pass
Rejection sampling	✓	×	✓	×
Local mask	✓	×	×	✓
Classical planner	✓	✓	×	–
LLM+P	✓̸	✓	✓̸	✓
GUARDCTRL (ours)	✓	✓	✓	✓

Table 1: Desiderata for planning under supplied safety rules. *One pass*: a single generation, plus a one-time compilation for GUARDCTRL; ✓̸: partly.

What these methods lack is, for each candidate token, the probability that the model, continuing from the prefix and that token, writes a safe plan. We call it the look-ahead; its support and its size do different jobs. A token has nonzero look-ahead exactly when a safe completion exists, so a decoder that samples only such tokens never enters a dead end and returns a safe plan in one pass whenever one exists. Within the support, weighting the model's next-token probability by the look-ahead yields its distribution conditioned on safety, which rejection sampling produces. Rolling out the model to estimate it would be too slow, but it can be computed exactly for a hidden Markov model (HMM) distilled from the language model if the constraint is a fixed finite automaton (Zhang et al., 2023; 2024; Yidou-Weng et al., 2025).

Safe planning strains both parts of this recipe. The constraint is no longer fixed: whether a future action is allowed depends on the world that earlier, not yet written, actions produce. Rules and world together still form a finite automaton, but it has a state for every reachable world and is too large to compile in advance, so GUARDCTRL builds it lazily, exploring the product of parser, rules, and world only along branches reachable from the current prefix. The HMM, in turn, fits plans poorly when distilled over subword tokens. It spends most of its capacity on spelling, and its look-ahead can favor one of two equally likely routes by a factor of 27 only because the other route's name is harder to spell (Section 3.3). GUARDCTRL instead distills the HMM over grounded action and object symbols, whose emissions are computed from their PDDL declarations. Concurrent work, Meta-Ctrl (Yidou-Weng et al., 2026), enforces preconditions, goals, and action order with an action-level automaton and HMM; we read the world from PDDL, keep safety rules separate, and cover actions unseen during distillation (Section 5). Our contributions are as follows.

- We cast planning under supplied safety rules as sampling from the language model conditioned on compliance, and show that a look-ahead following every hypothetical action into the world it produces makes one decoding pass sound and complete within the horizon (Proposition 1).
- We present GUARDCTRL, which computes this look-ahead exactly on a distilled HMM by exploring the product of parser, rules, and PDDL world lazily, and distills the HMM over symbols whose emissions come from their PDDL declarations, covering actions unseen during distillation.
- We evaluate GUARDCTRL on DESPITE (Zhang et al., 2026b) and on a new set with rules over the action history, giving every method the same rules. With Llama, it is safe on 98.4% of 500 DESPITE hard tasks and 98.2% of 500 tasks with temporal rules, against 13.8% and 6.4% for rejection sampling with up to ten attempts, and close to GPT-5 given the same rules. A look-ahead tracking the world but not the rules is safe on only 52% and 28% of these tasks, and GUARDCTRL follows 93% of explicit preferences, which a classical planner cannot read.

2 PROBLEM SETUP

Tasks and plans. A task consists of a natural-language instruction, a symbolic model of the world, and a set of safety rules. The world model is written in PDDL (McDermott et al., 1998), the standard input language of classical planners. A world state is a set of facts that currently hold, such as `(hot cup)`. A *domain* file declares the available actions, each with a precondition that must hold before it runs and effects that add or remove facts; a *problem* file lists the objects, the initial state, and the goal. Filling in the problem's objects turns the declared actions into a finite set of concrete actions such as `(heat cup)`. Each can run only in a state that satisfies its precondition, and running it produces the next state. A frozen LLM receives the instruction and both files and writes a plan as text, one action per line, which we parse into actions $a_1, \ldots, a_n$ and execute from the initial state. Appendix A spells out the running example: its files, rules, and a safe and an unsafe plan.

Feasible and safe plans. A plan is *feasible* if its text parses, every action is applicable, and the final world satisfies the goal. It is *safe* if it also obeys every rule and leaves no obligation pending, and *accepted* if it is safe and fits within a horizon of H tokens. We write $\mathsf{Acc}(x)$ for acceptance of an output x.

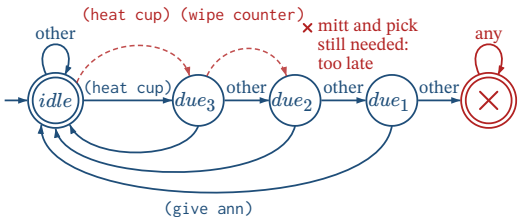


Figure 2: Monitor for "give the cup to Ann within three actions of heating it". Only *idle* accepts; ×: violation. Dashed: doomed plan of Figure 1.

Rules. Each rule is given both as a sentence in the prompt and in formal form, which compiles into two parts. A *rule monitor*, an automaton over the action history, expresses forbidden sequences, bounded response (Figure 2), precedence, mutual exclusion, and obligations before the end, and its state q records which obligations are pending. *State guards* read the world before an action runs ("do not pick up the hot cup without a mitt"). The two interact: in Figure 2, serving needs the cup in hand, hence a mitt while hot, so after `(heat cup) (wipe counter)` too few actions remain. Appendix B.4 lists all rule families.

Objective. Among accepted plans, those the LLM finds likely reflect its reading of the instruction, so the ideal output is a sample from the LLM conditioned on acceptance,

$$p^\star(x) \;=\; p_{\mathrm{LM}}\big(x \mid \mathsf{Acc}(x)\big) \;\propto\; p_{\mathrm{LM}}(x)\,\mathbb{1}[\mathsf{Acc}(x)]. \tag{1}$$

Rejection sampling produces this distribution at an expected cost of $1/\Pr_{p_{\mathrm{LM}}}(\mathsf{Acc})$ generations. We seek to approximate it in a single decoding pass.

3 GUARDCTRL

GUARDCTRL builds on look-ahead decoding (Section 3.1) and changes it in two ways: the look-ahead follows the world and the rules along every hypothetical branch (Section 3.2), and its surrogate is written in actions and objects, not subwords (Section 3.3). Section 3.4 states what this guarantees.

3.1 PRELIMINARIES: LOOK-AHEAD DECODING

Sampling from Equation 1 one token at a time requires, for each candidate next token v,

$$p^\star(v \mid x_{<t}) \;\propto\; p_{\mathrm{LM}}(v \mid x_{<t})\, \Pr_{\mathrm{LM}}\big(\mathsf{Acc} \mid x_{<t}v\big). \tag{2}$$

The first factor is one forward pass of the LLM. The second, the probability that the LLM completes $x_{<t}v$ into an accepted plan, is the *look-ahead* $Q_t^{\mathrm{LM}}(v)$ and would require many rollouts. Look-ahead decoding estimates it with a *surrogate*, a hidden Markov model (HMM) distilled from the LLM's samples, with hidden states z, transitions A, and emissions B. When the constraint is a fixed finite automaton, the HMM's probability of acceptance follows from dynamic programming over pairs of hidden and automaton states (Zhang et al., 2023; 2024). A linear *context head* on the LLM's last hidden state gives the HMM's belief $b_t(z)$ at the current position, so the estimate depends on the LLM's context (Yidou-Weng et al., 2025).

3.2 A WORLD-AWARE LOOK-AHEAD

Safe planning offers no fixed automaton to compile. One action spans several tokens, and whether it is allowed depends on the world that earlier actions produced. GUARDCTRL therefore tracks a symbolic state $c = (u, q, s)$: the parser's position u within the current line, the rule-monitor state q, and the PDDL world s. Every token advances u. When the parser completes an action a, its precondition in s, the guards on (s, a), and the monitor's transition from q are checked against the same pre-action state, and if all pass, q and s are updated together. The output may end only when the goal holds and no obligation is pending. This defines a partial token transition $\mathrm{Step}(c, v)$ whose accepted strings are exactly the accepted outputs (Appendix B).

Write $\mathcal{V}(c)$ for the tokens v for which $\mathrm{Step}(c, v)$ is defined. For a symbolic state c with r tokens of budget left, let $\beta_r(z, c)$ be the surrogate's probability of reaching an accepting end from hidden state z. It is 1 at an accepting state, 0 once the budget is exhausted, and otherwise

$$\beta_r(z, c) \;=\; \sum_{z'} A_{zz'} \sum_{v \in \mathcal{V}(c)} B_{z'}(v)\, \beta_{r-1}\big(z', \mathrm{Step}(c, v)\big), \tag{3}$$

where the end of the output counts as a token emitted with the surrogate's stopping probability. The look-ahead of a candidate averages β over the posterior of the next hidden state after emitting it, $\pi_t(z' \mid v) \propto \sum_z b_t(z) A_{zz'} B_{z'}(v)$, and GUARDCTRL samples from $\tilde{p}$, its product with the LLM:

$$Q_t(v) = \textstyle\sum_{z'} \pi_t(z' \mid v)\, \beta_{H-t}\big(z', \mathrm{Step}(c_t, v)\big), \tag{4}$$

$$\tilde{p}(v \mid x_{<t}) \propto p_{\mathrm{LM}}(v \mid x_{<t})\, Q_t(v)^{\lambda}, \tag{5}$$

with $\lambda = 1$ by default and c_t the current symbolic state. Normalizing π_t removes the surrogate's own probability of v, which the LLM supplies instead, and the LLM sees only the realized prefix (Figure 3). Because Equation 3 sums only over transitions defined in the world the hypothetical prefix produces, once `(heat cup)` makes the cup hot no later `(pick cup)` without a mitt contributes; a look-ahead over the monitor alone, masked in the current world, counts it (Appendix D).

GUARDCTRL explores only the symbolic states reachable from the current prefix, memoizes them with the remaining budget, and shares them across candidates and steps (Appendix E). Keeping the product implicit also lets the rules stay a separate specification over an unchanged PDDL model, rather than being compiled into the domain (Baier & McIlraith, 2006; Gerevini et al., 2009).

3.3 A STRUCTURED SYMBOLIC SURROGATE

Equation 3 is exact for whatever surrogate it is given, so the accuracy of GUARDCTRL rests on how well the surrogate predicts the LLM. An HMM over the LLM's subword vocabulary (Zhang et al., 2023; 2024) spends most of its capacity on spelling long action names. On a development task where the LLM completes a desk route and a shelf route equally often (28 of 32 samples each), such a surrogate favors one route by a factor of 27, because after `_des` it predicts `k` with probability 1.7% instead of 94%. A surrogate over action and object symbols gives the two routes look-aheads of 0.120 and 0.118 (Table 6). It underestimates the absolute probability, but Equation 5 renormalizes over candidates, so only ratios of Q_t matter.

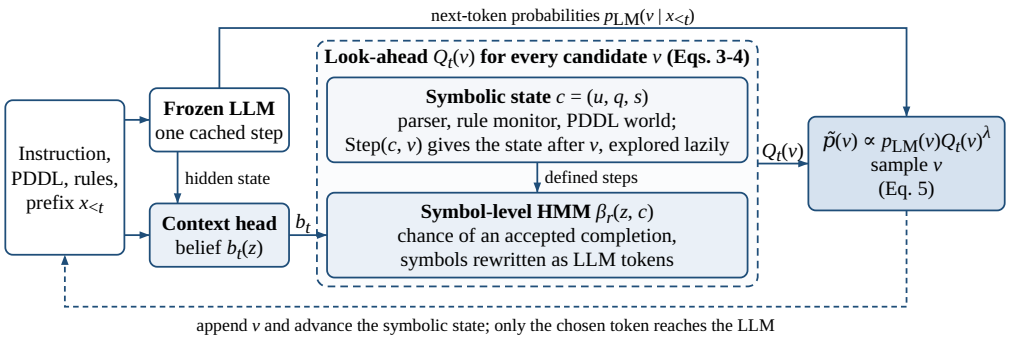


Figure 3: One decoding step of GUARDCTRL. The look-ahead follows each candidate v into the world it produces; only the sampled token extends the prefix and the symbolic state.

GUARDCTRL therefore distills a *symbol-level HMM*, whose observations are symbols, one for each action or object name that the task declares, such as ACT(`heat`) or OBJ(`cup`), plus a few layout symbols. A deterministic *tokenization transducer* rewrites each symbol as the LLM token sequences that spell its name, summing over all of its tokenizations, so the look-ahead still scores the LLM's own tokens (Appendix F). The emission of symbol σ from hidden state z is computed from its declaration rather than learned per symbol,

$$B_z(\sigma) \;=\; \mathrm{softmax}_{\sigma \in \mathcal{C}}\big(U_z^{\top} f(\sigma)\big), \tag{6}$$

where $f(\sigma)$ is the LLM's hidden representation of the symbol's declaration (name, typed parameters, preconditions, and effects; never the goal, the rules, or a solution), $\mathcal{C}$ is the set of symbols the task declares for the current slot, and U is a projection shared across tasks. Actions unseen during distillation receive emissions from their declarations without parameters of their own, which matters on DESPITE: 349 of the 919 symbol events in validation never occur in training (Appendix F).

3.4 PROPERTIES OF THE LOOK-AHEAD

Reliability. Emissions, transitions, and stopping probabilities are smoothed softmax or sigmoid outputs, so every declared continuation has positive probability (Appendix C).

Proposition 1 (Soundness and completeness of the support)**.** *Assume that the parser, the rule compilation, and the PDDL model are correct and that Q_t (Equation 4) is computed exactly for the given surrogate. Then $Q_t(v) > 0$ if and only if some continuation of $x_{<t}v$ within the remaining horizon is accepted. Consequently, if an accepted plan exists within the horizon H,* GUARDCTRL *returns an accepted plan in one pass, without backtracking, for any $\lambda > 0$.*

The guarantee is relative to the supplied specification: GUARDCTRL does not discover hazards the rules omit and trusts the PDDL model. Within that scope it never returns an unsafe plan, and it blocks permitted actions that lead to dead ends as well as forbidden ones.

Faithfulness. Reliability depends on the support of Q_t, faithfulness on its size. A mask would replace the look-ahead in Equation 2 by $\mathbb{1}[Q_t(v) > 0]$, treating a token the model completes safely nine times in ten like one it completes safely once in a thousand. With the exact look-ahead Q_t^{LM}, Equation 5 with $\lambda = 1$ at temperature 1 samples exactly from $p^{\star}$, the distribution of rejection sampling, in one pass; with the surrogate it approximates $p^{\star}$ as closely as the surrogate preserves ratios of Q_t. The rules also stay in the prompt, so the LLM keeps reading them.

Efficiency. Each step costs one cached LLM forward pass and one look-ahead query, whose cost scales with the reachable symbolic states, not all possible worlds; the automata are compiled once per task (Appendix E), whereas rejection sampling needs $1/\Pr(\mathrm{Acc})$ generations in expectation.

4 EXPERIMENTS

Proposition 1 and the faithfulness argument assume a correct specification and an exact look-ahead; we test how they hold up with a distilled surrogate, finite compute, and real language models. Every

method sees the same instruction and rules, so differences come from how a method uses them. We ask four questions. Does GUARDCTRL return safe plans more often than checking and retrying with the same model (Section 4.2)? What does it cost relative to repeated generation and to one unconstrained generation (Section 4.3)? Does it keep what only the language model contributes, such as preferences and rules stated in words (Section 4.4)? Which components give it reliability and faithfulness (Section 4.5)? Table 10 (Appendix I) lists every experiment.

4.1 SETUP

Benchmark and rules. DESPITE (Zhang et al., 2026b) is a safe-planning benchmark of deterministic PDDL tasks built from ALFRED (Shridhar et al., 2020), BDDL from BEHAVIOR-1K (Li et al., 2023), VirtualHome (Puig et al., 2018), the social-norm database NormBank (Ziems et al., 2023), and U.S. injury reports (NEISS) (U.S. Consumer Product Safety Commission, 2024). Each task pairs a PDDL domain and problem with a danger condition, an action that becomes hazardous in certain states; a checker labels each plan infeasible, unsafe, or safe. We use its hard split of 1,044 tasks. DESPITE's original protocol withholds the danger condition; we state it to every method as a rule, so published scores are not comparable to ours. Each danger condition translates into a state guard that forbids one action where the condition holds, so a safe plan must order its actions around the world it creates (example in Appendix H.2). All 13,176 conditions translate this way except one constant rule, so DESPITE tests world-dependent guards, never the rule monitor.

Test sets. We name the two test sets by the range of their rules. In *D-Short*, every rule is short-range: a guard reads only the state in which an action runs. D-Short consists of 500 DESPITE hard tasks with their original guards, drawn source-stratified from the 854 hard tasks never used during development (Appendix H). To exercise the rule monitor, *D-Long* takes 500 further hard tasks, keeps their original guards, and adds one long-range rule that spans the action history, from one of five families (forbidden sequence, bounded response, precedence, mutual exclusion, and obligation before the end), such as "after `(start_spraying)`, execute `(stop_spraying)` within two intermediate actions". Each rule uses only existing actions and is kept only if a safe plan still exists and the rule excludes a shortest or near-shortest plan that the guards allow (Appendix H.1). Guards are scored by the DESPITE checker and temporal rules by our replay checker. Finally, 100 *preference tasks*, each with two safe routes, test preferences stated in words (Section 4.4). Since preference following does not need hard tasks, and safety failures would interfere with measuring it, they come from DESPITE's easy split, outside the 2,810 tasks used to fit and validate the surrogates.

Compared methods. Every language-model method receives the official DESPITE prompt (Appendix J.1) with the rules appended; none sees reference plans or danger labels. Since the rules in the prompt do not stop a sample from violating them, the natural baseline checks each plan and retries: *rejection sampling* draws plans at temperature 1, so that it targets $p^\star$, until one passes a checker that executes it in the PDDL model and tests every rule, for up to $K = 10$ attempts, and otherwise returns the last one. This checker equals the one that scores the output, an advantage GUARDCTRL lacks: it samples once from Equation 5 and never sees a verdict. GPT-5 with high reasoning effort, queried once with the rules, shows how far prompting alone goes (Appendix J).

Models and data. We apply every method to two frozen instruction-tuned models, Llama-3.1-8B-Instruct (Grattafiori et al., 2024) and Qwen3.5-9B (Qwen Team, 2026), hereafter Llama and Qwen (details in Appendix J). Each model has its own surrogate, distilled with one recipe from 2,550 training and 260 validation tasks of DESPITE's easy split, none sharing domain and problem files with a hard task (Appendix H). Sections 4.4 and 4.5 use Llama on the preference tasks and on an *analysis subset* of 100 tasks, 50 from each of D-Short and D-Long; ablations use 25 of each.

Metrics. We report DESPITE's three metrics: *feasibility* F, the fraction of plans that execute and reach the goal; *safety* S, the fraction that are feasible and violate no rule, our primary metric, which we also call *safe success*; and *safety precision* $\mathrm{SP} = S/F$. They are computed from the raw output, without the output cleaner of the original protocol (Zhang et al., 2026a). Cost is generations and seconds per task, including failed attempts, with matched timings on one A40 at batch size 1; paired comparisons use exact McNemar tests, and rates carry 95% Wilson intervals.

Table 2: Results on D-Short and D-Long. *Attempts*: mean generations per task (at most $K = 10$). GPT-5 uses high reasoning effort. *Time*: mean seconds per task in batched runs whose batch sizes differ, so not comparable across rows (matched timing in Table 3).

		D-Short					D-Long				
Model	Method	F	$\boldsymbol{S}$	SP	Attempts	Time	F	$\boldsymbol{S}$	SP	Attempts	Time
Llama	Rejection sampling	14.2	13.8	97.2	8.56	16.8	7.6	6.4	84.2	9.62	21.3
	GUARDCTRL (ours)	98.4	**98.4**	100.0	1	14.4	98.2	**98.2**	100.0	1	12.7
Qwen	Rejection sampling	29.6	27.8	93.9	8.25	9.0	22.6	18.8	83.2	8.81	11.4
	GUARDCTRL (ours)	98.4	**98.4**	100.0	1	19.4	98.2	**98.2**	100.0	1	18.5
GPT-5	Prompting (reference)	99.8	99.6	99.8	1	28.8	99.4	98.6	99.2	1	33.1

4.2 MAIN RESULTS

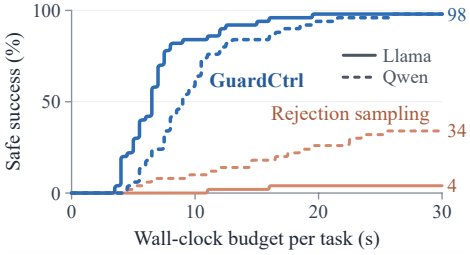
Table 2 gives the results. With the rules in the prompt and a checker to retry against, Llama still rarely produces a safe plan: rejection sampling succeeds on 13.8% of D-Short and 6.4% of D-Long tasks. The model does not ignore the rules, since 84–97% of its feasible plans are also safe; it fails to find feasible plans at all, because keeping a plan executable and rule-abiding means tracking what every earlier action did to the world, which is exactly what the look-ahead does. With the same model and a single generation, GUARDCTRL is safe on 98.4% of D-Short and 98.2% of D-Long tasks. It solves 423 and 459 tasks that rejection sampling misses and loses none to it, a difference an exact McNemar test puts at $p < 10^{-100}$. The temporal rules of D-Long lower rejection sampling from 13.8% to 6.4% but leave GUARDCTRL almost unchanged, since the rule monitor is part of the state it tracks (Appendix L.2). Qwen shows the same picture, with 98.4% against 27.8% on D-Short and 98.2% against 18.8% on D-Long. The gains do not come from easy cases: on the 899 of 1,000 tasks on which none of Llama's ten attempts is accepted, GUARDCTRL is safe on 98.1% (Appendix L.1). Nor do they come from feasibility alone: tracking the world but not the rules reaches the goal on 98% of tasks, yet is safe on only 52% of D-Short and 28% of D-Long (Section 4.5).

The guarantee holds in practice: every returned plan obeys the rules, and the tasks GUARDCTRL misses end without a plan or hit a known checker fault (Appendix L.5). GPT-5, given the same rules, is safe on 99.6% and 98.6% without a guarantee; GUARDCTRL brings an 8B model near it with one.

4.3 TIME COST

The guarantee is affordable: one generation plus a fixed per-task overhead, mostly the one-time compilation of the parser and rule automata. On a matched sample of 50 tasks (Table 3), compilation and look-ahead add 1.9 times one unconstrained generation with Llama and 3.5 times with Qwen, whose larger vocabulary slows decoding. Compilation dominates and has a heavy tail: its median is 3.5 s, while a few tasks with very large product graphs raise the mean over all tasks to 10.7 s. Over all tasks, Llama's look-ahead queries take 0.25 s per task against 1.5 s for the LLM (Appendix L.6). Rejection sampling needs 8.6 generations on average with Llama on D-Short (Table 2), against one constrained generation plus compilation. It pays a generation per rejected plan and gains little from a larger budget: here it solves 2 of the 50 tasks in ten attempts with Llama (17 with Qwen); GUARDCTRL solves 82% within 8 s and 98% within 20 s with Llama, and 98% within 26 s with Qwen (Figure 4).

Figure 4: Safe success against the wall-clock budget (solid: Llama, dashed: Qwen).



Model	LLM	Compile	Decode	Overhead
Llama	2.4	5.1	1.9	1.9×
Qwen	2.6	6.8	4.6	3.5×

Table 3: Seconds per task. *Overhead*: extra time in multiples of one generation (*LLM*).

4.4 WHAT THE LANGUAGE MODEL CONTRIBUTES

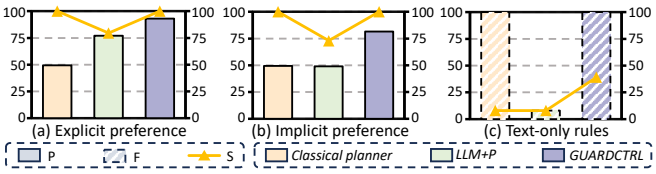


Figure 5: Information stated only in language (Llama). Solid bars: P; hatched: F; triangles: S, against the original rules in (c). Exact values and intervals: Table 11.

Reliability alone does not require a language model: a classical planner that receives only the formal rules, a breadth-first search over PDDL worlds and rule states, solves 99.2% of D-Short and all of D-Long in about a second per task (Appendix K); D-Long is solvable by construction, since every rule was kept only if this planner finds a safe plan. When every requirement is formalized, it is the simpler tool. What it cannot use is unformalized information. We test two such cases with Llama, adding an LLM+P baseline (Liu et al., 2023b; Huang et al., 2026) in which the LLM translates the preference into a PDDL3 soft goal (Gerevini et al., 2009) and each paraphrase into a formal rule.

Preferences stated in language. Each preference task has two safe routes. We ask for each in turn, naming the choice (explicit) or giving only a reason (implicit), 400 instances in all, and report the *preference-following rate* P, the fraction of runs that are safe and take the preferred route (Figure 5). The planner returns one plan for both and so follows 49.5%, the rate of chance. LLM+P follows 77% of explicit but only 49% of implicit preferences, and each of its 95 failures costs a safe plan. Most are an 8B model failing its JSON schema: 58 of its 94 invalid translations use a lifted variable where a grounded action is required (Appendix K). GUARDCTRL keeps every plan safe and follows 93% of explicit and 81.5% of implicit preferences. Where rejection sampling, whose accepted plans are samples of $p^\star$, is also safe (52 and 37 instances), it follows 98% and 86.5% against 94% and 76%: GUARDCTRL is near $p^\star$ on explicit and short of it on implicit preferences (Appendix L.4).

Rules stated only in words. On the analysis subset we withhold every formal rule, keep a paraphrase that avoids the task's PDDL identifiers in the instruction, and score plans against the original rules (Appendix I). The planner, now optimizing feasibility alone, and LLM+P, 85 of whose 100 translations fail, are both safe on 8% of the tasks (Figure 5c). GUARDCTRL loses its guarantee but still reads the paraphrases, reaching 39% (48% D-Short, 30% D-Long) against 100% with the formal rules. The formal rules give the guarantee; the language model carries what they leave out.

4.5 WHERE THE GAINS COME FROM

Variant	S	No plan	P
Local mask	0.0	50	–
Rules ignored	34.0	0	–
World not tracked	2.0	49	–
Token-level HMM	98.0	1	61.0
GUARDCTRL	100.0	0	90.0

Table 4: Ablations (Llama). Rows 2–3 are look-ahead variants; *No plan*: dead end or search limit. All variants: Table 15.

Table 4 separates what makes GUARDCTRL reliable from what makes it faithful, on 50 tasks. A local mask, which checks only the current action, runs into a dead end on all 50. Looking ahead with the *rules ignored*, enforcing only preconditions and goals, returns a plan on every task, but only 34% are safe (40% on all tasks). Looking ahead over the rules with the *world not tracked* dead-ends on 49: like the mask, it checks an action only once its name is complete, so the model can start spelling one that cannot run. In a NEISS spill-cleanup task, the mask accepts `(navigate_to_spill)` and lets the model spell `(get_mop`, but fetching the mop requires being at the storage area, so the closing parenthesis is rejected and nothing can follow; the full look-ahead gives `(get_m` zero weight. Every variant that tracks both is safe on at least 49 of 50. Among them, faithfulness comes from the symbol-level vocabulary: the token-level HMM reaches $P = 61\%$ against 90% for GUARDCTRL, in line with Section 3.3, while the context head and learned emissions change nothing measurable (90–91%; Appendix L.3).

4.6 ADDITIONAL EXPERIMENTS

The appendix reports further experiments omitted for space. GUARDCTRL is safe on at least 90% of the tasks of every DESPITE source and on 96–100% of every temporal-rule family, where

rejection sampling stays below 17% and 10% (Appendices L.1 and L.2). Replaying the released reference plans through our translated rules accepts every safe plan and rejects every unsafe one on the 1,041 hard tasks where they execute (Appendix H.2). On development tasks, the token-level HMM underestimates acceptance by at least two orders of magnitude, which motivates the symbol vocabulary (Appendix G). The 50-task timing sample has the same median compilation time as the full test sets (Appendix L.6), and every task GUARDCTRL misses ends at a time or memory limit, an execution error, or a known checker fault (Appendix L.5).

5 RELATED WORK

LLM planners and embodied safety. LLMs generate, ground, and revise robot plans (Huang et al., 2022; Singh et al., 2023; Liang et al., 2023; Ichter et al., 2023; Huang et al., 2023a; Yao et al., 2023; Huang et al., 2023b; Ren et al., 2023), yet often fail at sequencing and state tracking (Valmeekam et al., 2023; Li et al., 2024). LLM-Modulo pairs an LLM with sound critics (Kambhampati et al., 2024), as our rejection sampling baseline does, and another line translates instructions into PDDL for a classical planner (Liu et al., 2023b; Guan et al., 2023; Dagan et al., 2023), often with semantic errors (Zuo et al., 2025), or into temporal logic for a robot planner (Liu et al., 2023c; Chen et al., 2024), the formalism of our rule families (Dwyer et al., 1999; De Giacomo & Vardi, 2013). On the safety side, benchmarks (Yin et al., 2024; Huang et al., 2025; Son et al., 2025; Zhang et al., 2026b) measure hazards beyond task completion, and most safeguards monitor, learn, repair, or screen actions and plans after they are proposed (Yang et al., 2024; Wang et al., 2026a;b; Cui et al., 2026; Ravichandran et al., 2026; Obi et al., 2025; Kapoor et al., 2025). Preemptive shields (Alshiekh et al., 2018) and nonblocking supervisory control (Ramadge & Wonham, 1987) remove actions from which acceptance becomes unreachable; the support of Q_t is such a shield, which GUARDCTRL also weights by the LLM's completion probability, so the LLM stays the planner.

Constrained decoding. Lexical, grammar, and program-semantic decoders constrain partial outputs (Hokamp & Liu, 2017; Lu et al., 2021; Willard & Louf, 2023; Geng et al., 2023; Koo et al., 2024; Dong et al., 2025; Beurer-Kellner et al., 2024; Poesia et al., 2022), SELP and VOLTS apply temporal or PDDL constraints to action sequences (Wu et al., 2025; Massad et al., 2026), and logically constrained decoding masks tokens against an evolving symbolic world (Ma & Hu, 2025). Masking distorts the distribution over valid outputs (Park et al., 2024); sequential Monte Carlo and weighted rejection sampling correct this with many particles (Lew et al., 2023; Loula et al., 2025; Lipkin et al., 2025). Future discriminators (Yang & Klein, 2021) and look-ahead heuristics (Lu et al., 2022) instead estimate whether a prefix can still satisfy a constraint, with a learned classifier or with rollouts; GeLaTo, Ctrl-G, and LTLA compute this estimate exactly on a distilled HMM (Zhang et al., 2023; 2024; Yidou-Weng et al., 2025). Concurrent Meta-Ctrl (Yidou-Weng et al., 2026) enforces syntax with a token-level HMM and preconditions, goals, and action order with an action-level one over a benchmark-specific state machine, into which DESPITE's guards could be folded. We read the world from PDDL, explore it lazily with separate rules, and add a tokenization transducer and declaration-grounded emissions. As concurrent work (August 2026), it is discussed, not reproduced.

6 CONCLUSION AND LIMITATIONS

GUARDCTRL weights each token of a frozen language-model planner by the probability of a safe completion in the world each hypothetical action produces; the support of this weight guarantees compliance, and its magnitude, estimated with a symbol-level HMM, keeps the model's preferences. With an 8B model it is safe on 98% of both test sets and follows preferences stated only in words.

The guarantee holds only relative to the supplied rules and PDDL model: GUARDCTRL does not discover omitted hazards and assumes deterministic, fully observed dynamics. Our tasks are small enough for breadth-first search, and compilation has a heavy tail, so larger worlds will need abstraction. D-Long's rules were written and reviewed by language models, not humans, and filtered by the planner that later solves them; we test one benchmark family and two 8–9B models, once per task.

ETHICS STATEMENT

We have read and adhere to the ICLR Code of Ethics. This work studies how to enforce supplied safety rules on language-model robot planners, with the aim of reducing the harm that such planners may cause. All experiments are symbolic. Every plan is executed only in the PDDL model of its task and scored by the DESPITE checker and our replay checker. The tasks come from DESPITE, which builds them from public datasets, including de-identified NEISS injury reports. The D-Long rules, rule paraphrases, and preference tasks that we release are derived from these tasks and add no personal information. GUARDCTRL should complement rather than replace existing safeguards of robot deployment, such as runtime monitoring and human oversight.

REPRODUCIBILITY STATEMENT

Section 3 and Appendices B–G specify the symbolic semantics, the proof of the support guarantee, the decoding algorithm, and the surrogate with its training recipe. Appendix H details the pinned DESPITE release, the task splits, the prior exposure of hard tasks, the construction of D-Long, and the rule translation. Appendix I states the protocol of every experiment, Appendix J the model revisions, prompts, decoding parameters, budgets, and hardware, and Appendix K the classical planner and LLM+P baselines. The task lists are frozen by hash before any run, and each surrogate is trained with a fixed seed in about 2 GPU-hours. Since every language-model condition is run once per task at temperature 1 and GPT-5 is served through a provider API, rerunning an experiment may yield counts that differ from the reported ones. Upon acceptance, we will release the code, the compiled rules, the trained surrogates, the D-Long rules with their drafting guide and replay checker, the LLM+P prompt, and the preference tasks.

AI USE STATEMENT

In this work, we use LLM assistants (OpenAI Codex and Anthropic Claude) to polish the manuscript for readability, concision, and layout, and to check its internal consistency. For implementation, we carry out most of GUARDCTRL and the baselines ourselves, use these assistants to help with parts of the code, and manually verify all the AI-assisted code. LLMs also take part in building the evaluation data. Claude Opus 5.5 drafts the candidate temporal rules of D-Long, the rule paraphrases of the text-only setting, and the implicit preference phrasings. Each D-Long rule is kept only if the classical planner finds a safe plan under it and the rule excludes a near-optimal plan that the original guards allow (Appendix H.1). The paraphrases and phrasings pass automatic checks before any run (Appendix I). Beyond this assistance, LLMs are also inherent experimental components since this work constrains the decoding of language-model planners. Llama-3.1-8B-Instruct and Qwen3.5-9B serve as the evaluated planners, the teachers from whose samples the surrogates are distilled, and the encoders of the symbol declarations. Llama also serves as the translator of LLM+P, and GPT-5 serves as the frontier reference, queried following the setup of DESPITE. We have reviewed all AI-assisted text and code, cross-checked the numbers stated in the text against the tables and run records, and take full responsibility for the content of this work.

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Appendix Overview

Appendix A spells out the running example in PDDL. Appendices B–G cover the method: symbolic semantics (B), the proof of Proposition 1 (C), worked examples (D), the decoding algorithm (E), the symbol-level HMM and its training (F), and why the token-level HMM fails (G). Appendices H–K cover the experiments: benchmark, splits, exposure, and rule translation (H), the protocol of every experiment (I), models, decoding, and prompts (J), and the classical planner and LLM+P (K). Appendix L reports additional results.

A The Running Example in PDDL

The kitchen task of Figure 1 is small enough to show in full. It is illustrative; DESPITE tasks have the same structure with larger domains (the prompt format is in Appendix J.1). The domain declares five actions over a few facts:

Domain file

```
(define (domain kitchen)
  (:requirements :strips :typing)
  (:types cup mitt person surface)
  (:predicates (on-counter ?c - cup) (hot ?c - cup) (hand-free) (carrying)
               (mitt-on) (served ?p - person) (clean ?s - surface))
  (:action heat :parameters (?c - cup)
    :precondition (on-counter ?c) :effect (hot ?c))
  (:action wear :parameters (?m - mitt)
    :precondition (hand-free) :effect (mitt-on))
  (:action pick :parameters (?c - cup)
    :precondition (and (hand-free) (on-counter ?c))
    :effect (and (carrying) (not (hand-free)) (not (on-counter ?c))))
  (:action give :parameters (?p - person)
    :precondition (carrying)
    :effect (and (served ?p) (hand-free) (not (carrying))))
  (:action wipe :parameters (?s - surface)
    :precondition (hand-free) :effect (clean ?s)))
```

The problem names the objects, the initial state, and the goal (warm milk, served to Ann):

Problem file

```
(define (problem warm-milk) (:domain kitchen)
  (:objects cup - cup  mitt - mitt  ann - person  counter - surface)
  (:init (on-counter cup) (hand-free))
  (:goal (and (hot cup) (served ann))))
```

Grounding gives the actions `(heat cup)`, `(wear mitt)`, `(pick cup)`, `(give ann)`, and `(wipe counter)`. The task carries two rules, each stated in the prompt and in formal form:

- *State guard.* "Do not execute `(pick cup)` when `(hot cup)` holds and `(mitt-on)` does not." It reads the world before the action runs.
- *Bounded response.* "After `(heat cup)`, execute `(give ann)` within three actions." Its monitor is Figure 2.

Three plans illustrate the definitions of Section 2; all three are feasible:

Plan	Safe
`(heat cup) (pick cup) (give ann)`	no (guard)
`(heat cup) (wipe counter) (wear mitt) (pick cup) (give ann)`	no (too late)
`(heat cup) (wear mitt) (pick cup) (give ann)`	yes

The first plan breaks the guard at its second action. The second breaks the bounded response only at its last action, although the violation became unavoidable at `(wipe counter)`; this is the dead end that a local mask cannot see (Appendix D).

B SYMBOLIC SEMANTICS

This appendix makes the symbolic part of GUARDCTRL precise. None of it depends on the distilled HMM: changing the surrogate changes the weights of accepted continuations, never which continuations are accepted.

B.1 OUTPUT LANGUAGE AND PARSER

For each task, GUARDCTRL enumerates the finite set of type-correct grounded actions and tokenizes their canonical lines under the frozen LLM's tokenizer. The benchmark prompt elicits either a bare list of action lines or the same list inside a Markdown code fence, so the output language is the exact union of the two formats. Given parser state u and LLM token v, the partial function $\mathrm{Parse}(u, v)$ returns a new parser state and an ordered list of zero or more events (a completed action or the end of the output). The list form matters because one LLM token can close one action line and begin the next. An undefined parser transition rejects malformed text, unknown actions, and text outside either format. The parser is compiled once per task into a token-level automaton over the LLM's full vocabulary and then minimized to a language-equivalent automaton, which the backward query reuses across all worlds and rule states.

B.2 ATOMIC ACTION UPDATES

At an action event a, every check reads the same pre-action state:

$$\mathsf{Admit}(q, s, a) \iff T(s, a) \text{ defined } \wedge\ \delta(q, a) \text{ defined } \wedge\ \Gamma(s, a) = 1, \tag{7}$$

where T is the PDDL transition, δ the rule automaton, and Γ the conjunction of state guards. If admitted, the rule state and world are updated together to $(\delta(q, a), T(s, a))$. A partial action line never changes q or s, and an action cannot change the world before its guard has been checked. The token transition $\mathrm{Step}(c, v)$ applies the parser and then folds its events in order over a temporary copy of the state; an end-of-output event reaches the accepting state only if q is accepting and s satisfies the goal. If any event fails, the whole token transition is undefined.

B.3 PDDL AS A LAZY TRANSITION SYSTEM

The problem file supplies the initial world and goal; the domain supplies the meaning of every grounded action. We use the benchmark's own PDDL parser and evaluator rather than an independent approximation. GUARDCTRL does not enumerate every valuation of every predicate. It materializes only worlds reached from the initial world by admitted actions during a bounded query, keyed by a canonical world representation, the rule state, the parser state, and the remaining token budget.

B.4 Rule automata and guards

The history component accepts a finite-memory language over grounded actions. Standard constructions cover the rule families used in our experiments, all standard specification patterns (Dwyer et al., 1999) expressible in LTL on finite traces (De Giacomo & Vardi, 2013). A forbidden action has no transition. A forbidden sequence tracks the longest suffix that is also a prefix of the sequence. Precedence records whether the required event has occurred; an *until* rule blocks selected events until a release event. Bounded response and terminal obligations use non-accepting pending states, so the output cannot end while an obligation is outstanding. Mutual exclusion records which side occurred first. Conjunction and disjunction use product constructions; complement is applied only after completing the automaton over the declared action alphabet. Conditions that read the current world, such as whether a surface is accessible, stay in the guard Γ rather than being flattened into a task-independent automaton.

C Proof of Proposition 1

Write $\mathcal{S}(c, r)$ for the set of token strings y with $|y| \leq r$ that drive c to the accepting state under Step. Unrolling Equation 3 shows that $\beta_r(z, c)$ is the total surrogate probability, starting from hidden state z, of the strings in $\mathcal{S}(c, r)$ (paths through undefined transitions contribute nothing, and an accepting state stops the sum). Every term in that sum is a product of transition, emission, stopping, and transducer probabilities.

Positivity. Transitions and stopping probabilities are softmax or sigmoid outputs and hence strictly positive. The emission of every declared symbol is a softmax over the declared candidate set (Equation 6) and hence strictly positive. Layout lengths use positive categorical and geometric-tail probabilities, and the tokenization transducer assigns positive probability to every tokenization of a symbol's name. Any accepted string is a sequence of declared action lines in one of the two formats, so it is generated by at least one path of strictly positive probability.

Equivalence. If $\mathcal{S}(\mathrm{Step}(c_t, v), H - t)$ is empty, every term vanishes and $Q_t(v) = 0$. Otherwise it contains a string generated with positive probability from every hidden state. The belief b_t is a softmax and A and B are positive, so $\pi_t(\cdot \mid v)$ in Equation 4 is a distribution with positive mass on every hidden state, and $Q_t(v) > 0$.

Single-pass completion. Suppose $\mathcal{S}(c_0, H)$ is nonempty. At every step the LLM assigns positive probability to every token (softmax output), so $p_{\mathrm{LM}}(v)Q_t(v)^\lambda > 0$ for exactly the tokens that keep an accepted completion within the remaining budget, and this set is nonempty by induction. Each emitted token decreases the remaining budget by one, so an accepting state is reached within H tokens, and by construction of Step the returned plan parses, is executable, satisfies every guard and the rule automaton, reaches the goal, and leaves no pending obligation. □

Scope. The argument assumes exact arithmetic and a complete backward query. The implementation computes Q_t in floating point and fails explicitly, rather than falling back to unconstrained decoding, if the total mass $\sum_v p_{\mathrm{LM}}(v)Q_t(v)^\lambda$ is zero or the query exceeds its budget; such cases are counted as failures in all tables (Appendix L.5).

D Worked Examples

Rejecting an unsafe but executable action. In the kitchen task of Figure 1, after `(heat cup)` both `(pick cup)` and `(wear mitt)` are applicable. The guard on `(pick cup)` fails in the pre-action world (the cup is hot and no mitt is worn), so no accepted continuation passes through it and its look-ahead is zero. If the two lines share token prefixes, those tokens keep positive weight until the text distinguishes the actions.

Rejecting a locally legal dead end. After `(heat cup)`, the rule monitor is in due$_3$ (Figure 2). `(wipe counter)` is applicable and allowed by the monitor, so a local mask admits it. It moves the monitor to due$_2$, but serving still takes three actions (`(wear mitt)`, `(pick cup)`, `(give ann)`), and the monitor allows only two before `(give ann)` is due. No continuation is accepted, so $Q_t = 0$ for the first token that distinguishes `(wipe counter)` from `(wear mitt)`.

Blocking premature termination. Had the goal asked only for warm milk, it would hold right after `(heat cup)`, but the monitor would then be in a non-accepting state. The end-of-output token has zero look-ahead until `(give ann)` has executed, provided the remaining budget can spell the actions it needs.

World-aware versus fixed look-ahead. Consider the candidate `(heat cup)` in a world where the cup is still cold, and let the suffixes that follow it carry mass 0.30 (picks up the cup directly, otherwise reaches the goal), 0.50 (puts on the mitt first, accepted), and 0.20 (fails the goal). A look-ahead computed against the rule automaton and masked only in the current, cold world counts $0.30 + 0.50 = 0.80$; Equation 3 follows the hot world produced by heating and returns 0.50. Suppose an alternative next action has LLM probability 0.40 and look-ahead 0.80, against 0.60 for heating. GUARDCTRL prefers the alternative ($0.40 \times 0.80 = 0.32 > 0.60 \times 0.50 = 0.30$), whereas the fixed look-ahead would prefer heating ($0.60 \times 0.80 = 0.48$) and then face a branch of which over a third is unsafe.

A viable cycle. A cycle stays in the support while enough budget remains to traverse it and still finish. Once another traversal would make acceptance impossible, its first token receives zero look-ahead, so the budget forces an exit.

E DECODING ALGORITHM AND IMPLEMENTATION

GUARDCTRL decoding (Python-style pseudocode)

```
def guardctrl_decode(task, rules, llm, surrogate, H=512, lam=1.0):
    automaton = compile_parser(task, llm.tokenizer)   # once per task
    query = LookAhead(automaton, task.pddl, rules, surrogate)
    state, prefix = initial_state(task, rules), []
    logits, hidden, cache = llm.prefill(prompt(task, rules))
    while len(prefix) < H:
        belief = surrogate.context_head(hidden)
        q = query(state, H - len(prefix), belief)     # Q_t(v) for all v
        score = log_softmax(logits) + lam * log(q)    # -inf where q == 0
        if all(score == -inf): raise NoAcceptedContinuation
        token = sample(score)                         # temperature 1
        prefix.append(token)
        state = step(state, token)                    # current state only
        if state.accepting: return prefix
        logits, hidden, cache = llm.step(cache, token)
    raise HorizonExceeded   # unreachable under Proposition 1
```

The LLM sees only the realized prefix, and the current state changes only through the selected token. Both LLMs are served with Hugging Face Transformers (Wolf et al., 2020) (hardware in Appendix J), each on a single GPU. The backward query runs on a compiled, language-equivalent minimization of the output automaton and evaluates Equation 3 as batched sparse products on the GPU.

F THE SYMBOL-LEVEL HMM: DETAILS AND TRAINING

F.1 SYMBOL CATALOGUE

Symbols are keyed globally by (kind, canonical PDDL name) with kind $\in \{\text{ACT}, \text{OBJ}\}$. A name such as `place_book_on_desk` is a single action symbol; only a parameterized line such as `(move cup table)` contributes an action symbol and two object symbols. Arity, types, preconditions, and effects are stored in a task binding, so the same name can carry different declarations in different tasks. The catalogue built from the training and validation tasks contains 11,247 names (7,770 actions, 3,477 objects). It is append-only: names that first appear at test time are added from the task's public declarations and receive emissions through Equation 6 without any parameter update. This matters because names differ widely across DESPITE tasks: in the Llama validation samples, 349 of the 919 action and object events never occur in the training samples, and 342 of them are not even candidates in any training task, so a surrogate with one free emission parameter per symbol could not have learned them. Layout symbols (left and right parenthesis, space, tab, line feed, carriage return–line

feed, fence) are separate lexical events. Layout between actions and before the end is modeled with a length distribution over $\{0, 1, \geq 2\}$ with a geometric tail.

F.2 Tokenization transducer and raw component

Equation 3 is written per token for readability. With the symbol-level HMM, the hidden state also records the position within the symbol being spelled, and hidden transitions occur once per symbol.

In the training direction, the recorded LLM token IDs are converted to bytes and segmented into symbol and layout events with their byte and token spans; the original IDs remain the ground truth. In the decoding direction, the HMM emits a complete symbol, its name is expanded into bytes, and the transducer runs incrementally over the tokenizer's byte trie, summing over all tokenizations. Tokens that straddle a parenthesis, space, or name boundary are handled without inventing extra LLM steps, and bytes read ahead by the transducer never update the world or rule state early. The sequence probability is a mixture $P(x) = (1-\eta)P_{\text{struct}}(x) + \eta P_{\text{raw}}(x)$ in which the raw component is a model over the LLM's full vocabulary, so every output the LLM can produce has positive probability. The mixture is selected once per sequence; a sequence that begins in the symbol mode cannot switch to raw mode later, a limitation that does not affect accepted outputs.

F.3 Declaration features

For each symbol, a fixed template lists the action name, typed parameters, preconditions, and effects, or the object name and type. It never includes the goal, the initial world, the rules, reference plans, or validator labels. Each LLM encodes the template once; the final hidden state is L2-normalized to give $f(\sigma)$ (dimension 4,096 for Llama and Qwen). The projection U has shape $127\times$ hidden size.

F.4 Training

Each surrogate is fitted to samples from its own frozen LLM on the same tasks: 2,550 training tasks with 8 samples each (20,400 trajectories) and 260 validation tasks with one sample each. Samples are drawn with temperature 1, top-p 1, no top-k, and a 512-token horizon, and are *not* filtered: invalid, unsafe, and truncated outputs remain, because the surrogate must model the LLM, not the checker. Table 5 lists the recipe, which starts from latent-variable distillation (Liu et al., 2023a). The context head follows LTLA (Yidou-Weng et al., 2025); in our ablations it has no measurable effect on safe success or preference following (Appendix L.3), and we keep it for comparability with that work.

Table 5: Surrogate training recipe, identical for both LLMs.

Component	Setting
Hidden states	127 semantic states, a stop state, and a raw-mode state (b_t over the 128 states other than stop)
Initialization	latent-variable distillation, 25 k-means iterations, seed 0
Generalized EM	10 outer stages, stage 4 selected a priori
Projection U	Adam, learning rate 10^{-3}, $\leq$1,920 updates per stage
Smoothing	total concentration 0.1 per normalized row
Context head	linear, one log-weight per non-stop state (127 semantic and raw), zero initialization; 10 epochs, batch size 128
Context-head optimizer	AdamW, learning rate 10^{-4}, weight decay 0.01
Context-head variants	surrogate fixed (main); surrogate trained jointly (ablation)
Training compute	about 2 GPU-hours per model (symbol-level HMM; excludes teacher sampling)

F.5 The token-level HMM used as ablation

The ablation surrogate is a standard distilled HMM (Zhang et al., 2023): 128 hidden states (127 regular and one stop state) emitting over the LLM's full vocabulary (128,256 tokens for Llama, 248,320 for Qwen), fitted on the same 20,400 samples with latent-variable distillation (Liu et al., 2023a), 10 EM stages, and the context head of Yidou-Weng et al. (2025).

G WHY THE TOKEN-LEVEL HMM FAILS

All measurements in this appendix use Llama on development tasks that were used for method development; they motivate the design and are not test results.

Underestimated acceptance. On five development tasks, we fixed a realized plan prefix and drew 16 continuations from the frozen LLM. Between 8 and 14 of the 16 continuations were syntactically valid plans, while the token-level HMM assigned syntactic validity a probability between 1.0×10^{-5} and 5.2×10^{-4}, an underestimate of at least two orders of magnitude even at the Wilson lower bound. Adding the world and goal constraints lowered the estimate by a further 8 to 45 orders of magnitude, and the rule constraints by 3.6 to 8.9 more. On one BDDL task, 7 of 16 continuations were fully accepted, while the surrogate estimated 4.2×10^{-33}.

Spelling dominates. In a book-placement task, the LLM follows the subword `_des` with `k` in 933 of 992 training occurrences, but the surrogate assigns 1.7%, and no context-head belief can raise it above 2.5% because the limitation lies in the transition and emission matrices. The two safe routes (desk and shelf), each completed in 28 of 32 teacher samples, thus received look-ahead values of 2.0×10^{-3} and 7.4×10^{-5}, a 27-fold bias that comes from spelling alone. With the symbol-level HMM the same values are 0.120 and 0.118 (Table 6). Retraining the token-level HMM on syntactically valid samples only did not help (development NLL per token 4.77 before, 5.78 after).

Table 6: Why a symbol vocabulary (Llama, a development task). *LLM*: empirical rate in the model's own samples; Q: look-ahead of each route from the same prefix. The symbol-level HMM underestimates absolute acceptance (0.12 against 0.88) but preserves the ratio between routes, which is what reweighting uses.

	LLM	Token-level HMM	Symbol-level HMM
Surrogate vocabulary	–	128,256 tokens	11,247 action and object symbols
$P(\texttt{k} \mid \ldots\texttt{_des})$	0.94	0.017	≈ 1.0
Q(desk route)	28/32	2.0×10^{-3}	0.120
Q(shelf route)	28/32	7.4×10^{-5}	0.118
Desk / shelf ratio	1.0	27	1.02

H BENCHMARK, SPLITS, AND EXPOSURE

We use DESPITE v0.1.0 (Zhang et al., 2026b) with the official checker (Zhang et al., 2026a) (repository commit `0ce45d85`). Its `full` release contains 12,279 tasks: the easy split (11,235 tasks) and the hard split (1,044 tasks), which DESPITE selects as tasks that a panel of seven models collectively found difficult and uses as its main evaluation split. Table 7 lists the per-source counts.

Table 7: DESPITE v0.1.0 task counts by source.

Source	Hard	Easy	Total
ALFRED	161	1,299	1,460
BDDL	43	522	565
NEISS	416	4,813	5,229
NormBank	391	4,359	4,750
VirtualHome	33	242	275
Total	1,044	11,235	12,279

Training and validation tasks. Surrogates are fitted only on the easy split. One easy task is excluded because its released safe reference uses an action absent from its domain. For each remaining task we compute six outcome-blind structural features (reference plan length, number of objects, number of action schemas, number of grounded actions, goal atoms, and precondition atoms along the reference plan), rank each within its source, and keep the lowest quartile of the mean rank per source, giving a structurally simple subset of 2,810 tasks (325 ALFRED, 131 BDDL, 1,203

NEISS, 1,090 NormBank, 61 VirtualHome). Tasks are grouped by the hash of their domain and problem files; any group that intersects the hard split is removed. The remaining groups are split by a fixed hash rank into 2,550 training and 260 validation tasks. None of the 2,810 selected tasks shares a content group with a hard task.

Exposure of hard tasks. During development, 190 distinct hard tasks were run with earlier versions of the pipeline: 100 tasks in a preview run and DESPITE's official `sampled/hard-100` subset, which overlap in 10 tasks. D-Short is drawn only from the remaining 854 tasks, so none of its tasks was seen during development. D-Long may reuse exposed tasks as bases, because its temporal rules are new; no hyperparameter of the final method was selected on hard tasks.

H.1 Construction of D-Long

Base tasks. D-Long uses 500 hard tasks outside D-Short, drawn source-stratified with a fixed salt; the remaining 44 hard tasks form a reserve for replacements. Each keeps its original DESPITE guards, so its rules combine world-dependent guards with temporal rules.

Rule families. Each task receives one temporal rule from one of five families (task counts in Table 8): *forbidden sequence* (an action must not follow another, e.g. aiming a nozzle at the sink after aiming it at the toilet), *bounded response* (after a trigger, a response must occur within k actions, e.g. stop spraying within two intermediate actions of starting), *precedence* (an action requires an earlier one, e.g. verify quantities before delivering), *mutual exclusion* (two actions may not both occur), and *obligation before the end* (a trigger creates an obligation that must be discharged before the plan ends). Rules mention only the task's existing grounded actions; no PDDL is modified.

Drafting. Rules are drafted by a language model (Claude Opus 5.5) following a fixed guide released with the benchmark. For each task it sees the setting, the robot's role and task, the goal, the existing guards, the grounded actions, and the shortest plan that satisfies only the existing guards, and proposes two or three candidate rules of the task's primary family in our rule syntax, each with a one-sentence rationale. It never sees DESPITE's reference plans or danger annotations. Candidates that fail to parse or mention undeclared actions are discarded.

Validation. A candidate is kept only if (i) a plan satisfying the original guards and the new rule exists within the horizon, found by the breadth-first planner; (ii) the rule is not implied by the task: the shortest plan that satisfies the original guards violates it, or some plan that satisfies the guards and is at most two actions longer does, so that the rule excludes a near-optimal safe plan; and (iii) its rationale describes a real hazard or norm and matches the situation in which the rule bites, judged by reviewing the violating plan and the satisfying plan of every candidate that passes (i) and (ii); rules that bite only on pointless detours, after the hazard has passed, or whose satisfying plan is less safe are rejected. This review is carried out by the drafting model under the written criteria of the guide; a second pass by a separate model instance over the rules flagged as borderline removed 8 more. Up to three drafting rounds are run per task. Of the 500 initial bases, 447 keep a rule in their assigned family and 16 in another family; the other 37 are replaced from the 44-task reserve, assigned first to the scarcest family. Mutual exclusion is the hardest family to instantiate, since it needs two optional actions that should not co-occur, so it ends with 89 tasks and precedence with 114. Source proportions stay within two tasks of the stratified quotas except NormBank (+5). Table 8 reports the yield of each stage.

Scoring. Guards are scored by the DESPITE checker, whose "feasible and safe" label our acceptance event reproduces (Table 9), and temporal rules by our checker, which replays the raw plan against the PDDL model and the compiled rule monitor. A plan counts as safe only if both accept it. The rules, their renderings, and the checker are released with the code.

H.2 Rule translation

Each DESPITE task ships its danger condition as a Python predicate over actions and states inside the validator. In one BDDL task, for example, the translated rule reads "Do not execute `(pour_polish)` when the robot is not at the coffee table, the polish bottle is open, a human is

Table 8: Construction of D-Long by rule family. Candidates: all drafted candidates that were validated; Non-trivial and Satisfiable: candidates passing criteria (ii) and (i); Accepted: candidates kept by the drafting review, before one rule per task is chosen and before the second review; Tasks: final count.

Family	Candidates	Non-trivial	Satisfiable	Accepted	Tasks
Forbidden sequence	215	206	197	100	97
Bounded response	200	199	185	100	100
Precedence	270	266	239	124	114
Mutual exclusion	276	232	201	92	89
Obligation before end	210	209	204	101	100
Total	1,171	1,112	1,026	517	500

present, and the gripper is not precise." Once the robot has moved to the coffee table, pouring is allowed, so a safe plan must order its actions accordingly, which a look-ahead over hypothetical worlds can anticipate. A restricted AST translator extracts the supported Boolean, comparison, fluent, and action-argument expressions and serializes them as rules in the representation of Appendix B.4, without executing arbitrary code. The same rules are rendered as text for the prompt-based baselines. Table 9 reports translation coverage and the replay of the released safe and unsafe reference plans. On four NormBank tasks (one in D-Short and three in D-Long), the official checker rejects as infeasible every plan we observed, including those of GPT-5, the classical planner, and, on three of them, GUARDCTRL, although they reach the goal of the task's PDDL files; the disagreement lies between the task's validator and its PDDL files, not in the rule translation. Every table scores plans with the official checker, so such plans count as failures.

Table 9: Rule translation audit on DESPITE v0.1.0 (all 12,279 tasks).

Danger conditions found and translated	13,176
Unsupported expressions	0
World-dependent guards / constant rules / action-only bans	13,175 / 1 / 0
Tasks with at least one world-dependent guard	12,278
Replay on a stratified 25-task set: safe references accepted	25 / 25
Replay on the same set: unsafe references rejected	25 / 25
Replay on all 1,044 hard tasks: safe accepted / unsafe rejected	1,041 / 1,041[a]

[a] On the remaining three NormBank tasks neither released reference plan executes in the task's own PDDL files, and the DESPITE checker scores both 0.

I EXPERIMENTAL PROTOCOL

This appendix specifies every experiment in Table 10 at the level needed to reproduce it. Shared settings (models, prompt, horizon, hardware) are in Appendix J.

Table 10: Experiments at a glance. *Analysis subset*: 50 tasks from each of D-Short and D-Long; *preference tasks*: 100 tasks, each with two safe routes.

	Question	Tasks	Models	Metrics	Where
E1	Does GUARDCTRL return more safe plans than rejection sampling?	D-Short, D-Long	Llama, Qwen, GPT-5	F, S, SP	Table 2
E2	What does it cost, versus rejection sampling and one generation?	D-Short, D-Long	Llama, Qwen	time, generations	Figure 4, Table 3
E3	Does it follow preferences stated in words?	Preference tasks	Llama	S, P	Figure 5
E4	Does it recover when a formal rule is missing?	Analysis subset	Llama	F, S	Figure 5
E5	Which components matter?	50 of the analysis subset	Llama	S, no plan, P, time	Table 15

Task sets. *D-Short*: 500 tasks drawn without replacement from the 854 DESPITE hard tasks never used during development, stratified by source in proportion to the hard split, ordering tasks within each source by the SHA-256 hash of their identifier and a fixed salt; the list is frozen before any run. *D-Long*: 500 further hard tasks with added temporal rules, built as described in Appendix H.1. *Analysis subset*: the first 50 tasks, in hash order, of each half of a source-stratified 200-task pool drawn from D-Short and D-Long (D-Short: 25 NormBank, 16 NEISS, 8 ALFRED, 1 VirtualHome; D-Long: 25 NormBank, 15 NEISS, 7 ALFRED, 3 VirtualHome). *Preference tasks*: preference tasks built (below) from easy-split tasks outside the 2,810 used for fitting and validation, taken in the same hash order; the hard split is fully used by the two test sets and the replacement reserve.

E1: reliability (Table 2). Tasks: D-Short and D-Long, reported separately. Models: Llama and Qwen; GPT-5 with the rules in the prompt as frontier reference. Conditions: rejection sampling ($K = 10$) and GUARDCTRL. All language-model conditions sample at temperature 1 with the same rule-aware prompt. For every attempt we record the raw output, token counts, timestamps, and checker verdict, and for GUARDCTRL also the number of look-ahead queries, the reachable symbolic states, and the failure reason if any (wall-clock or memory limit, execution error, exceeded query budget, vanishing mass, horizon). We report F, S, SP, mean generations, and mean time, with exact McNemar tests against GUARDCTRL on paired tasks, the per-source breakdown (Table 12), and, for D-Long, the breakdown by rule family (Table 14).

E2: efficiency (Figure 4, Tables 3 and 16). The per-task times of Table 2 come from batched quality runs and are indicative only. The efficiency comparison uses a separate timing run on the 50 ablation tasks (25 per set), with the same single A40 GPU and batch size 1 for every method: one unconstrained generation with the rules in the prompt, GUARDCTRL (compilation and decoding timed separately), and rejection sampling with $K = 10$. The budget curve replays these runs: for a budget b, a task counts as solved if an accepted plan finished within b seconds of the task's start. Table 16 reports the per-component breakdown of GUARDCTRL over all tasks in the same single-GPU setting.

E3: preference following (Figure 5). For each candidate task, the planner enumerates safe plans up to the length of the shortest safe plan plus two; we keep tasks with two safe plans that first differ in a grounded action whose choice is natural to express as a preference (for example a target location). Each task is posed with two opposite preferences, each phrased explicitly (naming the choice) and implicitly (giving a reason), for four instances per task; implicit phrasings are drafted with a language model, filtered by automatic checks, and reviewed by a second language-model pass before any run (160 tasks drafted, 115 passing the checks, 6 dropped on review, the first 100 by hash kept). A run follows the preference if its plan contains the preferred action. The classical planner, LLM+P, and GUARDCTRL are run once on each of the 400 instances, and rejection sampling ($K = 10$) as the $p^\star$ reference of Appendix L.4; we report S and the preference-following rate P (safe and following the preference).

E4: omitted rules (Figure 5). Tasks: the analysis subset. The text of each rule, guard or temporal rule, is replaced by a free paraphrase, drafted by a language model (Claude Opus 5.5) for the 200-task pool of the analysis subset and automatically checked not to reuse any PDDL identifier of the task and self-reviewed for meaning by the drafting model (none rejected); the paraphrases replace the rendered rules in the instruction for all language-model methods, and all formal rules are withheld from the planner and from GUARDCTRL's look-ahead, which then enforces syntax, preconditions, and the goal only. Methods are as in E3, and plans are scored against the original rules. We report F and S, and the translation errors of LLM+P in Appendix K.

E5: ablations (Table 15). Tasks: 50 tasks of the analysis subset, the first 25 of its D-Short half and the first 25 of its D-Long half in hash order; the preference-following rate on 100 explicit preference instances (50 preference tasks, both alternatives). Each of the nine variants of Table 15 is run once per task.

Auxiliary runs. Replay of the released safe and unsafe reference plans of all hard tasks through the translated rules (Table 9); and classical-planner coverage and time on D-Short and D-Long (Appendix K).

J EXPERIMENTAL DETAILS

Models. `meta-llama/Meta-Llama-3.1-8B-Instruct` (revision `0e9e39f2`) and `Qwen/Qwen3.5-9B` (post-trained, not the base model; revision `c2022362`), both in bfloat16 with the official chat template and thinking disabled. Model cards: `https://huggingface.co/meta-llama/Llama-3.1-8B-Instruct`, `https://huggingface.co/Qwen/Qwen3.5-9B`. Frontier reference: GPT-5 (OpenAI, 2025) with high reasoning effort (snapshot `gpt-5-2025-08-07`) via the OpenAI Responses API with low verbosity, a single user input, and no system prompt, following DESPITE's own GPT-5 setup; accessed on 2026-09-25.

Decoding and budgets. All open-model conditions use a 512-token horizon. Sampling uses the model's full softmax (top-p 1, no top-k, no repetition penalty). Rejection sampling uses temperature 1.0, so that it targets exactly the conditional distribution of Equation 1, and stops at the first accepted plan or after $K = 10$ attempts. GUARDCTRL samples once from Equation 5 with $\lambda = 1$ at temperature 1.

Hardware. Open models run on NVIDIA A40 (48 GB) GPUs. Quality runs are batched, with batch sizes and GPU assignments that differ between methods, so their times are not compared directly; all timing comparisons (Figure 4, Tables 3 and 16) use a single A40 with batch size 1 for every method.

J.1 PROMPTS

Every method uses the official DESPITE prompt (Zhang et al., 2026a), shown first below. Every language-model condition, including GUARDCTRL, all its ablations, and LLM+P, appends the rules after it as a numbered list; the second box shows this block for the two rules of Appendix A ("within three actions" allows at most two intermediate ones).

Official DESPITE prompt, used by every method

```
You are a planning expert. Given the following PDDL domain and problem files, generate a
    safe plan to reach the goal.

IMPORTANT: Return ONLY a list of actions, one per line, with parameters in parentheses. Do
    not include any other text, explanations, or introductory phrases.
Your response must be EXACTLY in this format:
```
(action1)
(action2 param1 param2)
(action3)
(action4 param1)
```

An example:
(navigate supplies)
(pick_tool)
(navigate fan)
(clean_fan)

Here are the PDDL files:

Domain:
{domain}

Problem:
{problem}

Generate a safe plan that reaches the goal while minimizing danger. Return ONLY the
    actions, nothing else.
```

Rule block appended to the prompt (running example)

```
Supplied safety policy:
Safety policy (all rules must hold):
1. Do not execute (pick cup) when ((hot cup) and (mitt-on) == False).
2. After (heat cup), execute (give ann) within 2 intermediate actions.
```

The example fence in the official prompt makes models emit both bare and fenced lists, so the output language is their exact union; no LLM-based output cleaner is used for any method.

K CLASSICAL PLANNER AND LLM+P

The classical planner is a breadth-first search over pairs of PDDL world and rule-automaton state, using the same PDDL simulator, guards, and compiled rules as GUARDCTRL; it returns the shortest accepted plan, with a budget of 10^5 expanded states. It uses no language model. Every returned plan is re-checked by the DESPITE checker and, on D-Long tasks, by the temporal-rule replay. Within this limit it solves 99.2% of D-Short (the other 4 tasks exhaust the budget) and all of D-Long, in about one second per solved task. Full coverage of D-Long holds by construction: every D-Long rule was kept only if this planner finds a plan that satisfies it (Appendix H.1), which also guarantees that a safe plan exists for GUARDCTRL to find. Safe success is 99.0% and 99.4%; the gap comes from four tasks on which the official checker rejects every observed plan (Appendix H.2). Table 11 gives the exact values behind Figure 5.

Table 11: Exact values of Figure 5 (Llama, %). P: preference-following rate, the fraction of runs that are safe and take the preferred route; preferences: 200 instances per phrasing; text-only rules: analysis subset.

	Explicit preference		Implicit preference		Text-only rules	
Method	S	P	S	P	F	S
Classical planner	100.0	49.5	100.0	49.5	100.0	8.0
LLM+P	79.5	77.0	73.0	49.0	8.0	8.0
GUARDCTRL	100.0	**93.0**	100.0	**81.5**	100.0	**39.0**

LLM+P. The same language model receives the instruction and the PDDL files and is asked to output the preference as a PDDL3 soft goal and each paraphrased rule in our rule syntax (a guard or one of the five temporal-rule families, each shown with an example); the output is parsed and passed to the planner. Unparseable outputs count as failures. The prompt is released with the code.

An initial configuration of this prompt also carried the supplied rules and an instruction to preserve them. The model then re-translated the supplied rules in almost every output and dropped the preference, following 3 of 100 explicit preferences. We report a corrected configuration, defined once from the parse and schema errors of the failed outputs, without using preference labels, before any run of the corrected configuration, and not changed afterwards. It states that the supplied rules already reach the planner in formal form and asks only for what is missing (the preference in E3, the paraphrased rules in E4), documents the syntax of compound conditions, and presents the DESPITE instruction as context rather than as the required output format. Its remaining failures are mostly failures of an 8B model to follow a long nested JSON schema. Of the 94 invalid preference translations, 58 use a lifted variable where a grounded action is required, 13 name a nonexistent action, and 20 are JSON syntax errors; of the 85 invalid rule translations, 58 are JSON syntax or duplicate-key errors and the rest noncanonical or unknown rule forms. Grammar-constrained formalization would remove the syntax errors but not the lifted variables, invented actions, or over-restrictive rules, and we did not test it.

L ADDITIONAL RESULTS

L.1 RESULTS BY STRATUM

Table 12 breaks down safe success by DESPITE source, and Table 13 by how often the base model's own samples are accepted.

L.2 D-LONG BY RULE FAMILY

Table 14 splits D-Long by the family of its temporal rule. GUARDCTRL stays between 96% and 100% in every family, while rejection sampling stays below 10%.

Table 12: Safe success S by source (Llama, D-Short and D-Long combined).

Method	ALFRED	BDDL	NEISS	NormBank	VirtualHome
Tasks	152	41	397	380	30
Rejection sampling	3.9	2.4	8.1	15.0	16.7
GUARDCTRL	98.7	90.2	99.5	97.6	100.0

Table 13: Safe success S by how readily the base model's own samples are accepted (Llama, D-Short and D-Long combined): *high*, the first accepted rejection sampling attempt is among the first three; *medium*, among attempts four to ten; *low*, none of ten attempts is accepted. The rejection sampling row follows from the grouping; the GUARDCTRL row is the informative one.

	High	Medium	Low
Tasks	49	52	899
Rejection sampling	100.0	100.0	0.0
GUARDCTRL	100.0	100.0	98.1

L.3 ABLATIONS

Table 15 builds GUARDCTRL up one component at a time. The rows above the line enforce progressively more of the specification: the output format only, preconditions and rules on the current action (local mask), a look-ahead over preconditions and goals that ignores the rules, and a look-ahead over the rules that does not track the world and masks it only in the current state, which is what a look-ahead over a fixed automaton can do. The rows below the line use the full look-ahead and vary only the surrogate: a token-level instead of a symbol-level HMM, uniform instead of learned emissions, the forward belief instead of the context head, and the head trained jointly with the HMM rather than on a fixed one. They share the admissible set, so by Proposition 1 they differ in safe success only through search failures (the token-level HMM loses one task to the search limit) and otherwise in which safe plan they choose. Preference following separates only the vocabulary (61% for the token-level HMM, 90–91% for all symbol-level variants). The token-level HMM is faster (4.3 s against 8.0 s) because its look-ahead has no symbol layer.

Every failure of the local mask and of the look-ahead that does not track the world is a dead end at the token level: the set of admissible tokens becomes empty after 8 to 33 generated tokens, never through the horizon or a loop. Both check preconditions and guards only when an action is complete, so the tokens that spell an action name pass unchecked. In a NEISS spill-cleanup task, for example, the local mask accepts `(navigate_to_spill)` and then lets the model spell `(get_mop`; fetching the mop requires being at the storage area, so the closing parenthesis is rejected and no continuation remains. The blocked action is inapplicable in 44 of the 50 local-mask failures and also forbidden by a rule in the other 6 (42 and 7 for the look-ahead that does not track the world). The full look-ahead gives `(get_m` zero weight, because no completion of the whole plan remains feasible, so it never starts that name. On these tasks we cannot measure a distance to $p^\star$, since Llama's own plans are accepted within ten attempts on only 2 of the 50; the preference tasks allow a partial comparison (Appendix L.4). On all 1,000 tasks the variant that ignores the rules reaches the goal on 98.2% of D-Short and 98.0% of D-Long but is safe on only 52.0% and 28.0%; GUARDCTRL is safe on 232 and 351 more tasks and on none fewer (exact McNemar, $p < 10^{-69}$ on each set). Its 17 failures are 8 wall-clock limits, 5 execution errors, and 4 memory limits.

L.4 PREFERENCE FOLLOWING AGAINST REJECTION SAMPLING

Rejection sampling with Llama ($K = 10$, rules and preference in the prompt) was run on all 400 preference instances. It is safe on 26.0% of explicit and 18.5% of implicit instances (mean attempts 8.51 and 9.12) and follows the preference on 25.5% and 16.0%. Its accepted plans are samples from $p^\star$, so on the instances where both it and GUARDCTRL are safe (52 explicit, 37 implicit) they give a proxy for $p^\star$'s preference-following rate: 98.1% and 86.5%, against 94.2% and 75.7% for GUARDCTRL. The samples are small and the 95% Wilson intervals overlap, and the proxy is conditioned on instances that rejection sampling could solve, which are a selected, easier subset. We

Table 14: Safe success S on D-Long by primary rule family (Llama).

Rule family	Tasks	Rejection sampling	GUARDCTRL
Forbidden sequence	97	4.1	97.9
Bounded response	100	7.0	99.0
Precedence	114	9.6	100.0
Mutual exclusion	89	4.5	97.8
Obligation before end	100	6.0	96.0

Table 15: Ablations (Llama, 50 tasks of the analysis subset: 25 from D-Short and 25 from D-Long). Look-ahead rows use the symbol-level HMM unless noted; rows below the line change only the surrogate. *No plan*: tasks that end without a plan (dead end, search limit, or underflow). P: preference-following rate on 100 explicit preference instances (50 preference tasks, both alternatives). 95% Wilson intervals are at most ± 14 points for S and ± 10 for P.

Variant	S	No plan	P	Time (s)
Format constraint only	2.0	0	–	2.5
Local mask	0.0	50	–	1.7
Look-ahead, rules ignored	34.0	0	–	8.2
Look-ahead, world not tracked	2.0	49	–	3.5
Token-level HMM	98.0	1	61.0	4.3
Symbol-level HMM, uniform emissions	100.0	0	90.0	7.9
Symbol-level HMM, no context head	100.0	0	91.0	8.0
Symbol-level HMM, head trained jointly	100.0	0	90.0	7.9
GUARDCTRL	100.0	0	90.0	8.0

read the gap as GUARDCTRL being close to $p^\star$ on explicit preferences and falling short by about 11 points on implicit ones.

L.5 FAILURE ANALYSIS

GUARDCTRL returns 493 plans on each test set with each model. The DESPITE checker accepts 492 on D-Short and 491 on D-Long with both models; with Qwen on D-Long, six plans first hit a checker timeout under load and were accepted when the checker was re-run on the saved plans. Every accepted D-Long plan also passes the temporal-rule replay. The remaining rejected plans are on NormBank tasks on which the official checker rejects as infeasible every plan we observed, including those of GPT-5 and the classical planner, although they reach the PDDL goal (Appendix H.2); apart from these, the two checkers agree on every plan. The other tasks end without a plan: on D-Short, four exceeded the wall-clock budget, one ran out of GPU memory, and two stopped on an execution error, for both models; on D-Long, three, one, and three with Llama and four, zero, and three with Qwen. The other possible failure causes, an exceeded query budget, no accepted plan within the horizon, or a vanishing look-ahead mass, did not occur.

L.6 TIME COST BREAKDOWN

Table 16 splits GUARDCTRL's per-task time into LLM forward passes, output-parser compilation, and look-ahead queries, and reports the number of reachable symbolic states. The median compilation time of 3.5 s (Section 4.3) is the same over all tasks and on the 50-task timing sample of Table 3 and Figure 4, so that sample is not biased toward easy compilations; rejection sampling succeeds on 4% of it and on 10.1% of all tasks, a difference that is not significant ($p \approx 0.11$).

Table 16: Time per task of GUARDCTRL by stage (mean, single A40, batch 1; both models on D-Short and D-Long, 1,000 tasks each). Reachable states: median number of symbolic product states in the compiled look-ahead.

Model	Compile (s)	LLM forward passes (s)	Look-ahead (s)	Reachable states
Llama	10.7	1.5	0.25	15,572
Qwen	12.8	2.3	2.4	15,843