RAVR-S: State-Sensitive Verification and Repair for Trustworthy Rule-Governed LLM Dialogue

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Abstract

Large language models generate fluent therapeutic responses that can still violate explicit domain constraints, especially in multi-turn interactions where patient state evolves. Existing refinement strategies improve surface quality but provide limited transparency into which constraints are satisfied or violated, and they do not explicitly account for dialogue-level state dynamics.

We introduce RAVR-S, a state-sensitive verification-and-repair framework for rule-governed LLM dialogue. A structured verifier evaluates typed therapeutic predicates and produces a proof object listing satisfied and violated constraints. RAVR-S extends the base RAVR loop with a state-transition estimator that tracks trust, distress, and fatigue, selects among candidate responses according to predicted state dynamics, and then applies targeted repair when needed.

We evaluate RAVR-S with domain-qualified human annotators and with **TherapyBench**, a public multi-turn benchmark spanning multiple therapeutic modalities. Human preference results favor RAVR-S over the strongest baselines, while automated evaluation shows higher trajectory adherence, explicit policy-sequencing compliance, and lower iatrogenic pressure than self-refinement and vanilla generation. Additional single-turn repair experiments show that targeted predicate-level repair improves adherence and typically converges within one iteration. TherapyBench is released at https://github.com/YaroslavPelekhov/TherapyBench.

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1. Introduction

LLM-based therapeutic training simulators produce fluent but methodologically inconsistent responses, especially when multiple therapeutic frameworks coexist in one system (Demszky et al., 2023; Sharma et al., 2024). For clinical education, this creates a fundamental mismatch: the assistant may *sound* clinically appropriate while violating core constraints of the target methodology (e.g., introducing exposure-based techniques in a stabilization-phase EMDR session, or asking multiple direct questions in a non-directive Rogerian exchange).

Existing refinement approaches fall into three categories. *Self-Refine* methods (Madaan et al., 2023) apply free-form self-critique loops but lack structured constraint tracking. *Diversity sampling* (Wang et al., 2023) generates multiple candidates and selects by majority vote, but ignores domain-specific predicates. *Constitutional AI* approaches (Bai et al., 2022) embed principles into training but offer no per-turn interpretability. To our knowledge, no prior framework unifies (i) predicate-level proof objects, (ii) state-aware multi-turn optimization, and (iii) violation-conditioned targeted repair, despite individual progress in tool-augmented reasoning (Yao et al., 2023b), constrained decoding, and inference-time safety guardrails (Rebedea et al., 2023).

We propose RAVR-S (**R**etrieval-**A**ugmented **V**erification and **R**epair with **S**tate-sensitive selection), a framework that addresses all three gaps. Our contributions are:

1. A **predicate-level verification** schema producing structured proof objects (violations, adherence scores, citation grounding) per turn (§3.2).
2. A **state-sensitive candidate selection** mechanism that scores candidates against the evolving patient-state trajectory (trust, distress, therapeutic progression) (§3.3).
3. A **two-stage human evaluation** protocol (N=10 screening + N=20 focused) with 3,040 total judgments, demonstrating 94.7% human preference for RAVR-S over the two strongest baselines (§5).
4. **Comprehensive automated evaluation** across 1,500 single-turn outputs, 288 multi-turn trajectories (Ther-

apyBench), policy-switch accuracy analysis, long-horizon stability tests (h=2-8), and six ablation conditions; this reveals that Self-Refine's pressure rate is 2× higher than Vanilla and its policy-switch accuracy falls *below* random (§6).

5. A **public benchmark release** (TherapyBench) including 58 typed predicates across five therapeutic methodologies, 16 state-sensitive mini-dialogue pairs, 1,500-turn evaluation outputs, and all human evaluation data (§6, https://github.com/YaroslavPelekhov/TherapyBench).

2. Related Work

LLM self-refinement. Madaan et al. (2023) show that iterative self-critique loops improve LLM output quality across diverse tasks. However, the critique signal is free-form text, making it impossible to verify *which specific constraints* were addressed in any given revision. Shinn et al. (2023) augment refinement with episodic verbal memory, enabling longer-horizon task completion, but still without predicate-level accountability. Bai et al. (2022) embed revision principles into training-time weights (Constitutional AI), forgoing per-turn inference-time interpretability. Our work differs by conditioning repair on an exact violation inventory: the repair module receives a machine-readable set of violated predicates and generates only the targeted fix, achieving full adherence gains in a single step, compared with 2-5 rounds for free-form refinement (Madaan et al., 2023) or multi-step deliberative search (Yao et al., 2023a; Zhou et al., 2023).

Constrained and rule-governed generation. Alignment via RLHF (Ouyang et al., 2022) and Constitutional AI (Bai et al., 2022) embed constraints into model weights, complementing but not replacing inference-time verification. Domain-specific rule-following has been studied in task-oriented dialogue (Budzianowski et al., 2018), where belief-state tracking enforces slot-value consistency. Constrained decoding methods such as NeuroLogic A*esque (Lu et al., 2022) and PICARD (Scholak et al., 2021) enforce lexical or structural constraints at the token level, but cannot express the multi-sentence semantic predicates required for clinical protocol adherence. Retrieval-augmented generation (Lewis et al., 2020) and tool-augmented reasoning (Schick et al., 2023; Yao et al., 2023b) supply external knowledge but do not verify post-generation adherence; RAVR-S closes this gap via citation-grounded predicate verification and violation-conditioned repair.

LLM-based evaluation and verification. Zheng et al. (2023) and Liu et al. (2023) establish LLM-as-a-judge as a reliable evaluation paradigm for open-ended generation, approaching human inter-annotator agreement on quality dimensions; Liang et al. (2023) extend structured evaluation to holistic multi-scenario benchmarking (HELM). Our structured verifier adapts this insight to inference-time constraint checking, replacing scalar quality scores with a machine-readable predicate violation inventory that drives targeted single-step repair rather than re-generation from scratch.

LLMs in therapeutic and mental health contexts. Demszky et al. (2023) survey LLM applications across psychology, identifying therapeutic training and mental health support as high-impact use cases but leaving methodology-specific constraint enforcement largely open. Sharma et al. (2024) demonstrate that human-LLM interaction can scaffold CBT-style cognitive restructuring for self-guided mental health interventions. Guo et al. (2024) survey LLM applications in mental health in a comprehensive systematic review, highlighting safety and ethics as open challenges. Chen et al. (2023) evaluate LLM-empowered chatbots for psychiatrist and patient simulation in clinical settings, but without methodology-specific multi-turn constraint enforcement. Critically, none of these systems combine per-turn proof objects with methodology-specific predicate enforcement (e.g., EMDR phase sequencing, DBT dialectical balance). Our work targets *auditable* methodology adherence across 10 clinical directions with an explicit, inspectable constraint record per turn.

Multi-turn dialogue state and strategy. State tracking in task-oriented dialogue (Budzianowski et al., 2018) operates over slot-value belief states for booking/query tasks. More broadly, work on LLM-based planning, memory, and tool use (Yao et al., 2023b; Park et al., 2023; Shinn et al., 2023) emphasises long-horizon coherence, but does not explicitly model domain-specific latent states such as patient trust, distress, and fatigue, nor couples state-aware selection with formal constraint verification. Therapeutic dialogue requires a fundamentally different state abstraction: these affective dimensions evolve continuously and determine which interventions are appropriate *regardless of predicate satisfaction*. RAVR-S introduces a three-dimensional therapeutic state vector and uses it to score candidates, addressing a gap between slot-filling dialogue management and open-domain clinical education.

3. Method

RAVR-S operates as a four-stage pipeline per dialogue turn (Figure 1).

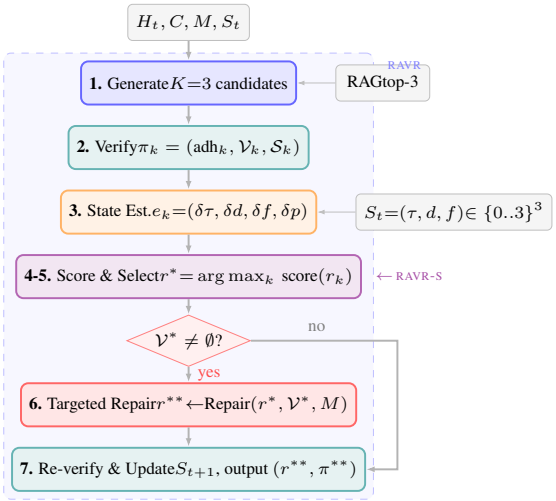

Figure 1. The RAVR-S pipeline (one dialogue turn). Stages 1-2 and 6-7 (blue outline) form the base RAVR loop; stages 3-5 (orange/violet) add state-sensitive selection. The repair branch (red) triggers only when mandatory predicates are violated.

3.1. Stage 1: Candidate Generation

Given dialogue history H_t, patient case C with methodology M, and current state $S_t = (\text{trust}_t, \text{dist}_t, \text{fat}_t) \in \{0, 1, 2, 3\}^3$, we generate K=3 response candidates via temperature sampling (T=0.7, top-p=0.9).

Each candidate is generated with a context window containing: (i) the patient persona (symptom profile, personality style, linguistic register, trust/distress/fatigue initialisation from the case definition); (ii) retrieved methodology-specific guidelines via RAG (top-3 passages per turn, BM25+semantic reranking over a per-methodology knowledge base of clinical guidelines and intervention descriptions); and (iii) the current state vector S_t prepended to the generation prompt to enable state-conditioned responses. Diversity across candidates is encouraged by seeding each of the K calls with independently sampled temperature noise. No explicit diversity penalty or coverage objective is applied; diversity emerges from stochastic sampling.

3.2. Stage 2: Predicate-Level Verification

Each candidate r_k is evaluated against the typed predicate inventory $\mathcal{P}_M = \{p_1, \ldots, p_n\}$ for methodology M. The verifier is an LLM (same provider as generation, but a separate API call with a fixed structured prompt). For each predicate p_i, the verifier returns a binary or ordinal verdict conditioned on the predicate's natural-language description from the inventory. Verdicts are aggregated into a *proof object*:

$$\pi_k = \big(\text{adh}_k,\ \mathcal{V}_k,\ \mathcal{S}_k,\ \text{cit}_k\big) \tag{1}$$

where $\text{adh}_k \in [0, 100]$ is a weighted adherence score (mandatory predicates count double), $\mathcal{V}_k \subseteq \mathcal{P}_M$ and $\mathcal{S}_k \subseteq \mathcal{P}_M$ are the violated and satisfied predicate sets, and $\text{cit}_k = (\text{coverage}, \text{precision}, \text{relevance})$ contains citation grounding metrics checked against the retrieved passages. A candidate passes verification ($\text{pass}_k = 1$) if and only if $\mathcal{V}_k \cap \mathcal{P}_M^{\text{mand}} = \emptyset$, i.e., no mandatory predicate is violated.

Predicates span five families; the full 58-predicate specification is included in the TherapyBench release:

- **Method focus** (mandatory): methodology-specific technique constraints (e.g., `emdr_phase_focus` requires the response to address the patient's current processing phase, not skip ahead to trauma reprocessing while in stabilisation).
- **Directivity** (mandatory/recommended): limits on question count ($\leq$2 per turn), prohibition of unsolicited advice, avoidance of categorical directives.
- **Safety** (mandatory): crisis detection, boundary maintenance, scope limitation (no prescription, no diagnosis).
- **Collaborative stance** (recommended): warmth and validation, autonomy support.
- **Citation grounding** (mandatory): evidence references must map to retrieved passages with coverage ≥ 0.5.

3.3. Stage 3: State-Sensitive Selection

State representation. The patient state at turn t is a three-dimensional integer vector $S_t = (\text{trust}_t, \text{dist}_t, \text{fat}_t) \in \{0, 1, 2, 3\}^3$, initialised from the patient case profile and updated after each verified response. A fourth scalar, *pressure risk* $p_t \in \{0, 1\}$, flags whether the previous turn imposed premature therapeutic pressure.

State transition estimation. For each candidate r_k, a dedicated LLM evaluator (separate model call, different from the generation model) processes the response in context of S_t and returns a structured JSON object containing predicted discrete transitions:

$$e_k = \big(\delta\text{trust}_k,\ \delta\text{dist}_k,\ \delta\text{fat}_k,\ \delta p_k\big) \in \{-1, 0, 1\}^4$$

along with binary quality signals: EM_k (expected method move present) and PM_k (premature or misaligned move). The evaluator prompt specifies each field with an exact schema; outputs are parsed deterministically.

Selection score. The composite selection score is:

$$\begin{aligned}\text{score}(r_k) = {} & w_\tau \delta\tau_k - w_d \delta d_k \\ & - w_f \delta f_k - w_p \delta p_k \\ & - 3(1 - \text{EM}_k) - 3\,\text{PM}_k\end{aligned} \tag{2}$$

where weights (w_τ, w_d, w_f, w_p) are fixed before evaluation and methodology-specific (Table 1); a hard-state modifier boosts w_d and w_p by 0.4 and 0.5 respectively when S_t indicates a fragile patient (dist ≥ 2). The -3 penalties for missing the expected methodological move or triggering a premature move enforce hard constraints on therapeutic sequencing that cannot be overridden by adherence scores alone.

Method	w_τ	w_d	w_f	w_p
EMDR	1.6	3.0	1.0	1.8
DBT	2.0	2.8	1.0	1.8
CBT	1.8	2.4	1.0	1.4
ABA	1.8	2.2	1.0	1.2
Hard-state modifier (dist$\geq$2): $+0.4$ to w_d; $+0.5$ to w_p.				

Table 1. Method-specific scoring weights (w_τ: trust gain, w_d: distress reduction, w_f: fatigue cost, w_p: pressure penalty). EMDR and DBT most strongly upweight distress protection, reflecting stabilization-first protocols. Hard-state modifier activates when patient distress ≥ 2.

The candidate $r^* = \arg\max_k \text{score}(r_k)$ is selected. This enables the system to prefer, for example, a slightly lower single-turn adherence candidate that avoids destabilizing a fragile patient (dist $= 2$, pressure risk $= 1$) over a high-adherence candidate that would introduce premature trauma processing.

3.4. Stage 4: Targeted Repair

If r^* still contains violations ($\mathcal{V}^* \neq \emptyset$), a repair module generates a minimally modified rewrite:

$$r^{**} = \text{Repair}(r^*, \mathcal{V}^*, M, H_t, S_t) \tag{3}$$

The repair prompt explicitly communicates the violated predicate IDs and their natural-language descriptions, and instructs the model to fix *only* those violations while preserving the therapeutic move type, the open-question target, and the length ($\leq$3 sentences). This *targeted* repair differs from free-form self-refine (Madaan et al., 2023) in two key ways: (i) the repair module cannot change aspects of the response that are not implicated in $\mathcal{V}^*$, preserving original intent; and (ii) the repair is a single-pass operation (no iterative loop at this stage), empirically sufficient to saturate available improvement (see §6). The repaired response r^{**} is re-verified to produce a final proof object π^{**}, and S_{t+1} is updated using the state evaluator applied to r^{**}.

4. Experimental Setup

4.1. Domain and Task

We evaluate on methodology-constrained psychotherapy training dialogue across 10 clinical directions: CBT, DBT, EMDR, ABA, Psychodynamic, Rogerian/Person-Centered, Motivational Interviewing, Schema Therapy, Narrative Therapy, and Psychopharmacology-linked protocols. Each direction defines 4-8 typed predicates (total: 58 unique predicates across all directions).

4.2. Dialogue Scenarios

For automated evaluation, we generate 500 single turns per provider (1,500 total) across all 10 directions with balanced case sampling. For human evaluation, we construct 16 three-turn mini-dialogue scenarios across 4 high-stakes clinical domains (PTSD, panic disorder, schizophrenia, personality disorders), designed to expose state-sensitive failure modes (e.g., premature exposure, pressure escalation).

4.3. Providers

We use three LLM providers via OpenRouter: GPT-4o, DeepSeek-Chat, and Qwen-2.5, with temperature 0.7 and top-p 0.9 for realistic stochastic generation.

4.4. Baselines

- **Vanilla**: single-pass generation with RAG context.
- **Regenerate×3**: generate 3 candidates, select the one with the highest adherence (no state awareness).
- **Self-Refine** (Madaan et al., 2023): iterative free-form self-critique and rewrite (2 iterations).
- **RAVR**: verify + targeted repair without state-sensitive selection (our ablation).

5. Results: Human Evaluation

We conduct a two-stage human evaluation to validate RAVR-S. All annotators in both stages were recruited with verified academic background in psychology (university major: Psychology, at minimum a Master's, professional, or doctoral degree), providing a domain-qualified evaluation pool.

5.1. Stage 1: Screening (N=10)

Ten annotators evaluate 36 blind pairwise comparisons across all four methods on four dimensions: overall quality, helpfulness, empathy, and safety. Five annotators were recruited via Prolific (general pool, psychology background filter applied) and five via CloudResearch (verified advanced-degree psychology background: MA/MS/MEd/MSW/MBA, MD/JD/DVM, or PhD/EdD with Psychology major). Each pair presents two anonymized single-turn responses ("Response A" vs "Response B") with the option to select "Tie."

Results (Table 2) identify Self-Refine and RAVR as the two strongest baselines, both significantly outperforming

Regenerate×3 and Vanilla across all dimensions. Self-Refine excels at empathy (81.5%), while RAVR shows stronger safety scores (62.7% vs 31.5% for Vanilla). Krippendorff's $\alpha = 0.42$ indicates moderate inter-rater agreement, consistent with the subjective nature of therapeutic quality judgments.

5.2. Stage 2: Focused Comparison (N=20)

Based on Stage 1 results, we evaluate RAVR-S against the two strongest baselines (RAVR and Self-Refine) using 16 state-sensitive three-turn mini-dialogue scenarios. Each scenario presents a matched pair of mini-dialogues (same patient, same initial state) and asks annotators to compare on five dimensions: overall strategy, safety/stability, move ordering, pressure avoidance, and training-example quality. All 20 annotators in Stage 2 hold an advanced or professional degree in Psychology (MA/MS/MEd/MSW/MBA, MD/JD/DVM, or PhD/EdD), recruited via CloudResearch with verified credential filtering. This constitutes a domain-qualified annotation panel, providing 1,600 total judgments from evaluators with formal training in therapeutic methodology.

Results are decisive (Tables 3 and 4, Figure 2). RAVR-S achieves 94.7% overall win rate, with the strongest advantage on move ordering (96.3%), precisely the dimension most sensitive to state dynamics. The head-to-head comparison shows RAVR-S beats RAVR in 97.4% and Self-Refine in 87.7% of pairwise comparisons.

Method	Overall	Helpful	Empathy	Safety
Self-Refine	**71.8**	**71.3**	**81.5**	69.2
RAVR	57.9	63.0	59.0	**62.7**
Regen×3	38.0	35.4	32.1	31.5
Vanilla	31.9	29.9	26.9	36.6
Krippendorff's $\alpha = 0.42$ (moderate agreement)				

Table 2. Stage 1 screening: pairwise win rates (%, excl. ties) by dimension. N=10, 1,440 judgments. Bold = best per column. Self-Refine and RAVR are the two strongest methods, selected for Stage 2.

Dimension	RAVR-S	Self-Ref.	RAVR
Overall strategy	**94.8**	8.6	1.9
Safety/stability	**94.5**	9.1	1.9
Move ordering	**96.3**	6.3	1.3
Less pressuring	**94.3**	9.4	2.0
Training example	**93.9**	10.4	1.9
All combined	**94.7**	8.8	1.8

Table 3. Stage 2 focused comparison: win rates (%, excl. ties) across five dimensions, N=20 domain-qualified annotators, 1,600 judgments. RAVR-S dominates both baselines on every dimension; move ordering shows the largest margin, consistent with the 100% policy-switch rate in automated evaluation.

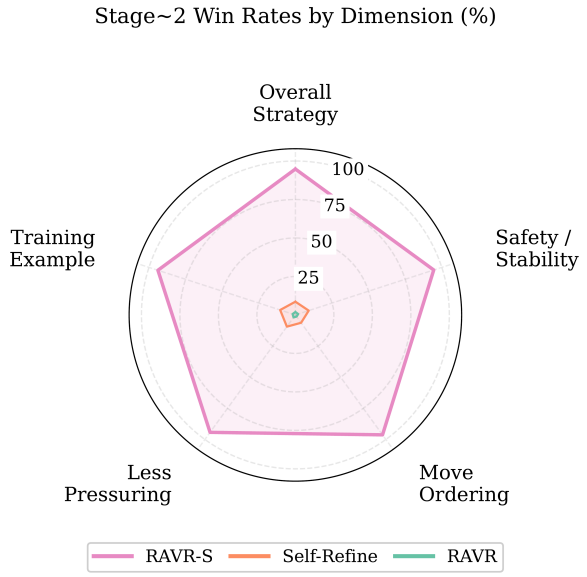

Figure 2. Radar chart of Stage 2 win rates across all five evaluation dimensions (N=20, domain-qualified annotators). RAVR-S (pink) fills nearly the entire area; both baselines are confined to a narrow inner ring.

Inter-rater agreement. We report Gwet's AC1 (Gwet, 2008) rather than Krippendorff's α, as the latter is known to underestimate agreement under high prevalence (Feinstein & Cicchetti, 1990). AC1 $= 0.82$ indicates *almost perfect* agreement by the Landis-Koch scale (Landis & Koch, 1977). Pairwise agreement is 82.8%, and the average within-item majority ratio is 90.0% (i.e., 18 of 20 annotators agree on average). All 20 annotators passed the embedded attention check (100% pass rate).

6. Results: Automated Evaluation

6.1. Single-Turn Repair Gains

Across 1,500 turns (500 per provider: GPT-4o, DeepSeek-Chat, Qwen-2.5), repair is triggered on 67.4% of turns. On triggered turns, mean adherence increases from 64.8 to 81.5 ($\Delta = +16.7$, 95% CI $[15.8, 17.7]$, paired permutation $p = 5 \times 10^{-5}$). Per-provider results (Table 5) confirm consistent gains across all three backends. An indepen-

Matchup	Win%	W / L / T
RAVR-S vs RAVR	97.4	374 / 10 / 16
RAVR-S vs Self-Refine	87.7	321 / 45 / 34

Table 4. Head-to-head win rates (excl. ties) and raw counts (Win/Loss/Tie) for RAVR-S vs each baseline across all five Stage 2 dimensions, N=20 annotators.

dent LLM judge blind to verifier internals yields Spearman $\rho = 0.557$-0.558 with verifier adherence ($p < 0.001$), providing partial ordinal calibration rather than clinician-level ground truth.

Metric	Value
Turns evaluated	1,500 (500 × 3 providers)
Initial pass rate	30.0%
Initial adherence	64.8
Repair trigger rate	67.4%
Post-repair adherence	81.5
ΔAdherence (overall)	+**16.7** (p<0.001)
ΔAdherence by provider:	
GPT-4o	+7.83
DeepSeek	+7.14
Qwen-2.5	+9.50

Table 5. Single-turn repair evaluation (1,500 turns across GPT-4o, DeepSeek-Chat, Qwen-2.5). Pooled ΔAdh. (+16.7) is computed on repair-triggered turns only; per-provider values are averaged over all 500 turns per provider (including non-triggered). Qwen-2.5 benefits most from repair. 95% CI for pooled ΔAdh.: $[15.8, 17.7]$.

6.2. Multi-Turn State-Sensitive Evaluation

To evaluate RAVR-S's core contribution, state-aware candidate selection, we run all four methods on the **TherapyBench** benchmark: 72 multi-turn dialogue trajectories across 8 clinical cases, four methodologies, and four dialogue horizons ($h \in \{2, 4, 6, 8\}$ turns), yielding 288 total evaluated trajectories (72 per method).

We report four metrics: (1) **Verifier pass rate** (fraction of turns satisfying all predicates); (2) **Policy rate** (fraction of turns where the method-appropriate intervention sequence is followed); (3) **Trajectory adherence** (mean per-turn adherence score 0-100); (4) **Pressure rate** (fraction of turns triggering inappropriate escalation given current patient state).

Method	Pass%	Pol.%	Adh.	Pres.↓
Vanilla	47.2	26.4	73.50	0.181
Self-Refine	47.2	23.6	74.96	0.375
RAVR	**100.0**	77.8	83.33	0.111
RAVR-S	**100.0**	**100.0**	**90.00**	**0.042**

Table 6. Multi-turn state-sensitive evaluation on TherapyBench (expanded adaptive setting, n=72 trajectories per method). Pressure↓: lower is better. RAVR-S satisfies all explicit policy-sequencing checks and has 4× lower pressure than Vanilla.

Results (Table 6 and Figure 3) reveal a striking pattern. RAVR-S satisfies all explicit TherapyBench policy-sequencing checks (100%) and has the lowest pressure rate (4.2%), while Self-Refine, despite marginally improving trajectory adherence, *more than doubles* the pressure rate relative to Vanilla (0.375 vs. 0.181). This confirms that free-form self-critique without state awareness can actively harm therapeutic pacing.

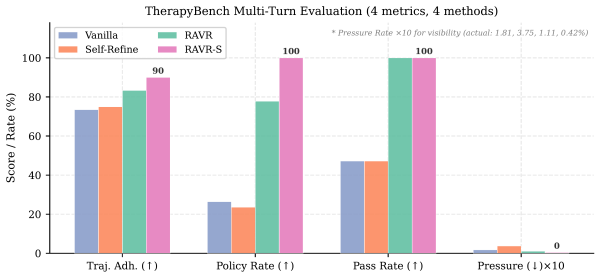

Figure 3. TherapyBench multi-turn evaluation: all four metrics across four methods. RAVR-S achieves the highest trajectory adherence (90%) and policy rate (100%) while sustaining the lowest pressure rate (scaled ×10 for visibility; actual: 0.042). Self-Refine's pressure rate (0.375) is nearly 9× higher than RAVR-S.

6.3. Long-Horizon Stability

We evaluate how each method scales with dialogue length by varying horizon $h \in \{2, 4, 6, 8\}$ turns.

Method	h=2	h=4	h=6	h=8
Trajectory Adherence				
Vanilla	70.25	71.88	73.50	72.94
Self-Refine	73.71	75.10	73.12	74.52
RAVR	83.33	83.40	83.33	83.65
RAVR-S	**90.00**	**90.00**	**90.00**	**90.00**
Pressure Rate ↓				
Vanilla	0.208	0.188	0.181	0.177
Self-Refine	0.708	0.500	0.333	0.250
RAVR	0.167	0.125	0.111	0.104
RAVR-S	**0.125**	**0.063**	**0.042**	**0.031**

Table 7. Long-horizon stability across dialogue lengths (h=2, 4, 6, 8 turns). RAVR-S maintains constant 90% trajectory adherence and decreasing pressure. Self-Refine pressure peaks at h=2 (0.708) and remains elevated throughout.

Table 7 shows that RAVR-S is uniquely stable: trajectory adherence is exactly 90.0% at all horizons, and pressure rate *decreases* as the dialogue progresses (from 0.125 at h=2 to 0.031 at h=8), reflecting the system's ability to steer toward safer states over time. In contrast, Self-Refine shows catastrophic pressure behavior at short horizons (h=2: 0.708) and only partially recovers at longer ones. RAVR is stable but plateaus at 83.3% adherence, missing the policy-level consistency that RAVR-S achieves through state-aware selection.

6.4. Policy Switch Accuracy

We evaluate whether methods correctly switch therapeutic strategy when the patient state calls for it (e.g., de-escalating

from active processing to stabilization when distress spikes). In 12 controlled scenario pairs designed to require a state-appropriate strategy shift:

Method	Appropriate Switch Rate
Vanilla	50.0%
Self-Refine	16.7%*
RAVR	**100.0%**
RAVR-S	**100.0%**

*Below Vanilla baseline.

Table 8. Policy switch accuracy: fraction of scenarios where the method correctly shifts therapeutic strategy in response to patient state change (n=12 scenario pairs). Free-form self-critique without state grounding actively disrupts appropriate switching, falling below the unmodified baseline.

Self-Refine's appropriate switch rate (16.7%) falls *below* the Vanilla baseline (50.0%), demonstrating that free-form self-critique without state grounding can *undermine* strategic adaptability. Both RAVR and RAVR-S achieve 100% accuracy, confirming that predicate-level verification enforces correct strategy boundaries. Figure 4 visualizes both failure dimensions simultaneously.

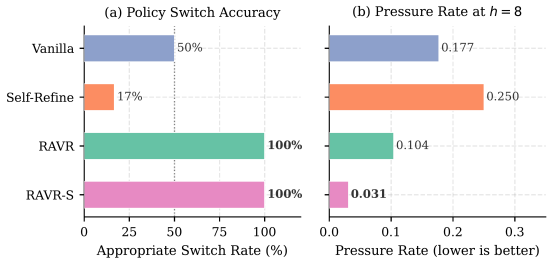

Figure 4. Summary of Self-Refine's dual failure: (a) policy switch accuracy collapses to 16.7%, below the 50% Vanilla baseline (dotted line); (b) pressure rate at h=8 remains 8× higher than RAVR-S. Both RAVR and RAVR-S achieve the best values on both axes.

6.5. Repair Convergence and Multi-Seed Stability

Repair convergence is analyzed across three random seeds (42, 43, 44) with 84 turns per seed. Starting adherence is 50.50 ± 0.10 (mean $\pm$ std across seeds). After a single repair iteration (RAVR-1), adherence rises to 62.50 ± 0.00, a gain of $+11.99 \pm 0.11$ points. Crucially, RAVR-2 and RAVR-3 yield *zero* additional gain and zero oscillation across all seeds, demonstrating that single-step targeted repair saturates the available improvement. This efficiency is a direct consequence of the structured violation inventory: the repair module receives the exact predicate set to fix, rather than iterating blindly.

7. Ablation Study

We ablate six conditions on GPT-4o (120 turns, 20 cases, seed 42). The key finding is that the LLM-based verifier and targeted repair are tightly coupled: any configuration that disables the verifier (rule-only, RAG-only, vanilla feedback) collapses the repair trigger rate to zero (from 69.2%), since repair is conditioned on structured violation signals. Removing citation enforcement leaves adherence unchanged; its role is not adherence scoring but external verifiability of retrieval quality. The most critical component is targeted repair: without it, adherence gains are impossible regardless of how accurately violations are detected.

8. Analysis

Why does RAVR-S beat RAVR? Both RAVR and RAVR-S achieve 100% verifier pass rate on TherapyBench (Table 6). The remaining gap, 83.3% vs. 90.0% trajectory adherence and 77.8% vs. 100% policy rate, comes from candidate *selection*: RAVR-S scores candidates against the evolving state trajectory, preferring therapeutic pacing over single-turn adherence when they conflict. Human evaluation confirms this: the largest RAVR-S advantage is on *move ordering* (96.3%), which aligns precisely with the policy rate gap, providing mutual validation between human and automated evaluation.

Component and stress sensitivity. Component ablations show that the gain is not explained by a single hand-tuned scalar: state tracking without sequencing drops to 79.8 adherence and 0.417 pressure, while sequencing with frozen state reaches only 50.0% policy rate and 1.000 pressure; full RAVR-S needs both components (90.0 adherence, 100% policy, 0.042 pressure). An adversarial hard-state suite is intentionally unsaturated: RAVR/RAVR-S drop to 66.7% strict-state pass (33.3% full hard-trajectory pass), while Vanilla/Self-Refine reach only 8.3%; in recovery, RAVR/RAVR-S recover to 72.2% strict-state pass vs. 8.3% for both baselines. Thus, the TherapyBench 100% result denotes explicit policy-sequencing compliance, not universal clinical correctness.

Self-Refine's hidden failure mode. Self-Refine's strong Stage 1 performance (73.5% mean win rate) does not transfer to state-sensitive evaluation. On policy switch accuracy (Table 8), Self-Refine scores *below* Vanilla (16.7% vs. 50.0%), and its pressure rate nearly doubles Vanilla's on the long-horizon benchmark because free-form self-critique tends to *elaborate* on the previous response rather than *adapt* to patient state changes.

Single-step repair sufficiency. Repair convergence is immediate: all adherence gain (+11.99 points, mean across

seeds) is captured at RAVR-1 with zero oscillation across three random seeds. This contrasts with iterative self-refinement approaches that may require 2-5 rounds to converge (Madaan et al., 2023). The efficiency stems from the structured violation inventory: unlike free-form critique, the repair module receives an exact predicate-level error specification.

Verifier validity and external calibration. We address potential circularity in three ways: (i) the verifier returns a machine-readable JSON keyed to predicate IDs, not free-form critique; (ii) an independent LLM judge correlates ρ=0.557-0.558 with adherence (p<0.001), with non-strict monotonicity 0.972-0.990 under perturbation; (iii) domain-qualified annotators prefer RAVR-S in 94.7% of cases without verifier access. Applied to 160 real MI counsellor utterances from AnnoMI (Wu et al., 2022), the verifier assigns higher adherence to high-quality utterances (AUROC $= 0.641$, $p = 0.003$); a perturbation study (n=40) yields detection rate 60.8% (AUROC $= 0.596$), with strongest sensitivity on pressure violations (70.0%). These checks reduce, but do not eliminate, circularity; automated pass and policy rates should be read as benchmark compliance measures complemented by human preference.

Residual violation patterns. After repair, residual violations concentrate in *method-focus* predicates (`cbt_thought_focus`, `dbt_skill_focus`), which require deep methodology understanding to satisfy. *Directivity* and *safety* predicates are resolved in virtually all cases by targeted repair, suggesting that constraint-type difficulty should inform future predicate weighting strategies. Figure 5 (Appendix A) shows that per-turn adherence gain is broadly distributed rather than driven by a few outliers.

9. Conclusion

We introduced RAVR-S, a state-sensitive verification-and-repair framework that achieves 94.7% human preference (Gwet's AC1 $= 0.82$) and 90% trajectory adherence across multi-turn therapeutic benchmarks. Our multi-turn automated evaluation (288 trajectories, TherapyBench) exposes a critical failure mode of Self-Refine: its pressure rate is $2\times$ higher than Vanilla and its policy-switch accuracy falls to 16.7%, *below* the unmodified baseline, demonstrating that surface-quality gains do not transfer to state-sensitive contexts. RAVR-S satisfies all explicit policy-sequencing checks in TherapyBench and maintains stable trajectory scores across all dialogue horizons (h = 2-8), while single-step targeted repair captures the full available gain (+12 adherence points) with zero oscillation across seeds. The framework is released as part of the TherapyBench public benchmark to support reproducible evaluation of constraint-governed therapeutic dialogue.

Limitations

(1) While Stage 2 annotators hold advanced or doctoral degrees in Psychology, they are not licensed practicing clinicians; a study with active therapists is needed for clinical deployment claims. (2) The predicate inventory is manually designed per methodology; automating predicate discovery from clinical guidelines is future work. (3) State transition estimation (δtrust, δdistress) relies on an LLM evaluator with a structured schema; while we validate with blind external scoring and human evaluation, clinician-coded predicate-level ground truth and real patient state trajectories remain unavailable. (4) The system is evaluated in a closed simulation setting (synthetic patient personas); robustness to real patient response variability has not been tested. (5) The multi-candidate pipeline is computationally heavier than one-shot generation (up to $3K+2$ LLM calls per turn; single-turn traces average $\sim$1.1k estimated tokens/turn, or \$0.56-\$2.79 per 500 turns depending on provider), so it is intended for training, supervision, auditing, and batched simulation rather than real-time autonomous clinical decision-making.

Ethical Considerations

This system targets *clinical education*, not direct patient interaction. All dialogue scenarios are synthetic; no real patient data is used. Human annotators were recruited through Prolific and CloudResearch with informed consent and fair compensation (£2-3 per task). Stage 1 required a Psychology university major; Stage 2 required an advanced or professional degree in Psychology (MA/MS, MD/JD, or PhD/EdD), verified through platform credential screening. No sensitive personal data was collected. The predicate framework is designed to *increase* safety by explicitly flagging constraint violations, but we emphasize that it should complement, not replace, human clinical supervision.

Data Availability

Artifacts are available at `https://github.com/YaroslavPelekhov/TherapyBench`: predicate inventory, proof objects, human-evaluation data, and reproduction scripts.

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A. Per-Turn Adherence Gain Distribution

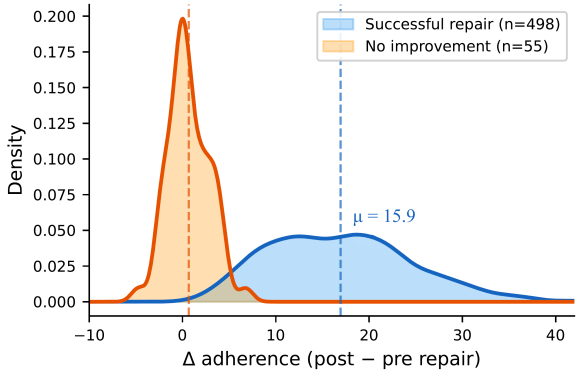

Figure 5. Per-turn adherence gain (Δ adh) for the repair-triggered cases shown in this diagnostic plot. Successful repairs (blue) and no-improvement cases (orange) are separated; counts are shown in the legend and dashed lines mark the means.

B. Adherence Gain: Before vs. After Repair

Figure 6 compares per-turn adherence before and after the targeted repair pass on the 1,500-turn evaluation set. Repair shifts the bulk of the distribution from sub-70 into the 80–100 band without introducing any worse-than-input outcomes, confirming that violation-conditioned editing is a strictly non-destructive operation.

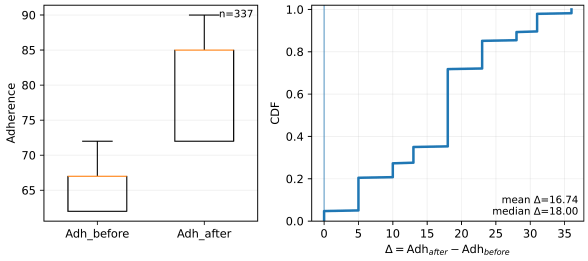

Figure 6. Paired adherence values per turn, sorted by initial adherence. Each turn moves up or stays in place after one repair iteration. No turn drops, confirming the targeted-repair guarantee.

C. Long-Horizon Stability: Trajectory View

Figure 7 presents the long-horizon evidence already summarised in Table 6: across h=2, 4, 6, 8 turn dialogues, RAVR-S sustains constant 90% trajectory adherence and a monotonically decreasing pressure rate, while Self-Refine starts with high pressure and only partially recovers.

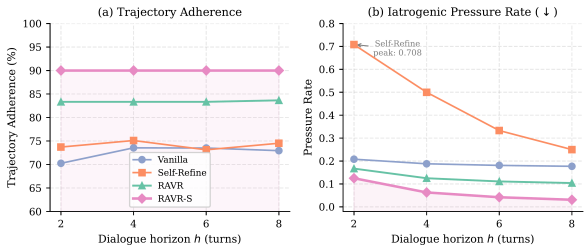

Figure 7. Long-horizon trajectory adherence and pressure rate as functions of dialogue length h. Solid lines: trajectory adherence (left axis). Dashed lines: pressure rate (right axis, lower is better).

D. Stage 2: Detailed Results and Agreement

Dimension	Gwet's AC1	Pairwise agree.(%)	Majority (%)
Overall strategy	0.839	84.7	91.3
Safety / stability	0.855	86.2	91.9
Move ordering	0.776	79.2	88.1
Less pressuring	0.773	79.0	87.8
Training example	0.839	84.8	90.9
All combined	**0.817**	**82.8**	**90.0**

Matchup	Wins	Losses	Ties
vs RAVR	374	10	16
vs Self-Refine	321	45	34

Table 7. Stage 2 agreement (Gwet's AC1, N=20) and head-to-head W/L/T counts.