

TIME: Temporally Intelligent Meta-reasoning Engine for Context Triggered Explicit Reasoning

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Abstract

Reasoning oriented large language models often expose explicit “thinking” as long, turn-global traces at the start of every response, either always on or toggled externally at inference time. While useful for arithmetic, programming, and problem solving, this design is costly, blurs claim level auditability, and cannot re-trigger explicit reasoning once the model begins presenting. Dialogue models are also largely blind to temporal structure, treating replies after seconds and replies after weeks as equivalent unless time is stated in text. We introduce TIME, the Temporally Intelligent Meta-reasoning Engine, a behavioral alignment framework that treats explicit reasoning as a context sensitive resource driven by discourse and temporal cues. TIME augments dialogue with optional ISO 8601 `<time>` tags, tick turns that represent silent gaps, and short `<think>` blocks that can appear anywhere in a reply. A four-phase curriculum including a small, maximally diverse full-batch alignment step trains Qwen3 dense models to invoke brief, in-place reasoning bursts and keep user facing text compact. We evaluate with TIMEBench, a temporally grounded dialogue benchmark probing chronology, commonsense under gaps and offsets, anomaly detection, and continuity. Across 4B to 32B scales, TIME improves TIMEBench scores over base Qwen3 in both thinking and no-thinking modes while reducing reasoning tokens by about an order of magnitude. Our training data and code are available at <https://github.com/The-Coherence-Initiative/TIME>, and TIMEBench is available at <https://github.com/The-Coherence-Initiative/TIMEBench>.

1 Introduction

Reasoning oriented language models increasingly make reasoning explicit by exposing thinking traces, often as chain-of-thought style text. In many systems, this reasoning appears as a long block at the start of each reply, either always on, or controlled externally through inference flags. The pattern boosts accuracy on arithmetic, programming, problem solving, and multi step planning, and it provides a practical interface for inspecting rationale when mechanistic interpretability is unavailable. Yet it also turns explicit reasoning into a blunt instrument.

Front loaded thinking has three recurring limitations. First, it is expensive and verbose, because the model emits many reasoning tokens even for trivial or low risk requests. Second, it weakens claim level auditability. A single monologue can loosely justify many later statements, so the mapping from an individual claim to its justification is often indirect. Third, it is not reactive. Once the model begins presenting, it cannot cleanly re enter a thinking phase to re check assumptions or re anchor itself if uncertainty arises mid answer.

A better target is a reasoning policy that is closer to human thought: short bursts, inserted where needed, and re-triggered when new cues appear. Achieving this requires signals that

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indicate latent state change, not only a task difficulty estimate. Temporal transitions are one of the most common such signals in real interactions. Plans expire, priorities change, and users return after long gaps. Yet unless time is stated explicitly, standard dialogue models treat a reply after two seconds and a reply after two weeks as the same token sequence.

We present **TIME** (Temporally Intelligent Meta-reasoning Engine), a behavioral alignment framework that equips reasoning models with context sensitive explicit thinking. TIME introduces three lightweight primitives: optional `<time>` tags on turns, optional short `<think>` blocks that may appear anywhere in a response, and tick turns that contain only time metadata to represent silence and passage of time. These primitives model temporality explicitly during training and evaluation, but timestamps are not required for the learned policy to operate: the model can still trigger brief reasoning from purely textual cues when temporal metadata is absent.

Because this behavior is rare in existing corpora, we align it with a four-phase curriculum on the Qwen3 family from 4B to 32B parameters. Early phases teach the model to parse the primitives and to keep reasoning bursts short and well delimited. A final phase uses a small but maximally diverse full-batch alignment set whose only invariant is contextually triggered reasoning keyed to temporal and discourse cues. This pushes the model toward a policy rather than a template, while reducing the tendency to collapse back into verbose, turn-global traces.

To measure reasoning competence under uncertainty and transitions as well as reasoning deployment, we introduce TIMEBench, a temporally grounded dialogue evaluation suite that probes chronological reconstruction, temporal commonsense under gaps and timezone shifts, detection of invalid or implausible timestamps, and continuity across long silences. Beyond task success, TIMEBench logs where and how often `<think>` blocks are used, enabling analysis of whether models reason only when the situation demands it.

2 Related Work

Temporal Cognition and Time-Aware Modeling

Prior work on time in language models primarily treats time as *content*: timestamped facts, event ordering, and knowledge that changes across time. Timestamp-conditioned modeling such as *Time-Aware LMs* [5] conditions generation on temporal indices to better handle drift and time-sensitive knowledge. Complementary analyses study temporal non-stationarity and *temporal generalization*, showing that performance degrades when models are evaluated on future slices beyond their training distribution [10]. More recent evaluation frameworks explicitly probe time awareness over large event collections, for example TimeShift-style methods that test recall and calibration under temporal constraints [7].

Benchmarks have also expanded from synthetic temporal arithmetic toward broader temporal competence. ChronoSense evaluates temporal relations and temporal arithmetic, while TimE and EvolveBench test temporal reasoning under real-world dynamics, including dialogue settings, invalid timestamp handling, and temporal misalignment between inputs and queries [8, 15, 18]. In parallel, retrieval and structured knowledge approaches incorporate temporal graphs to represent evolving facts, including temporal GraphRAG-style systems for time-sensitive retrieval and updates [6]. These lines strengthen temporal factuality, ordering, and retrieval, but still focus on time as part of the *world state*. In contrast, TIME uses elapsed time and temporal discontinuities as *interaction state*: a ubiquitous cue for latent context shifts that should trigger explicit reasoning, re-grounding, or brevity changes.

Explicit Reasoning Traces and Reasoning Control

Chain-of-thought prompting [14] improves multi-step task performance and provides explicit reasoning traces that are often treated as operational explanations. However, a growing body of work shows that such traces are not reliably faithful to the computations that drive final

answers, limiting their use as audit artefacts and motivating methods that measure or improve faithfulness [2, 3, 11, 13]. Beyond faithfulness, turn-global reasoning also creates practical issues: cost, latency, and weak claim-level attribution when a long rationale must justify many downstream statements.

Most deployed systems still treat explicit reasoning as a mode rather than a policy. Hybrid reasoners allow inference-time toggles, but the model itself does not decide when to reason. Recent work begins to learn this decision, for example by training hybrid-reasoning models to select whether to think, often using reinforcement learning or controller objectives [9]. Other approaches control *how much* a model reasons via length-conditioned policy optimization [1]. Orthogonally, methods such as DOTS search over reasoning action trajectories, and RL-based interleaving trains models to alternate thinking and answering to reduce time-to-first-token and improve efficiency [16, 17]. These advances show progress toward adaptive reasoning, but are typically framed around task difficulty, length budgets, or action planning, and often remain effectively turn-global at inference time. TIME targets a different axis: short, in-place reasoning bursts triggered by situational cues, including temporal transitions and discourse discontinuities, enabling mid-response re-anchoring when uncertainty or drift emerges.

3 Framework

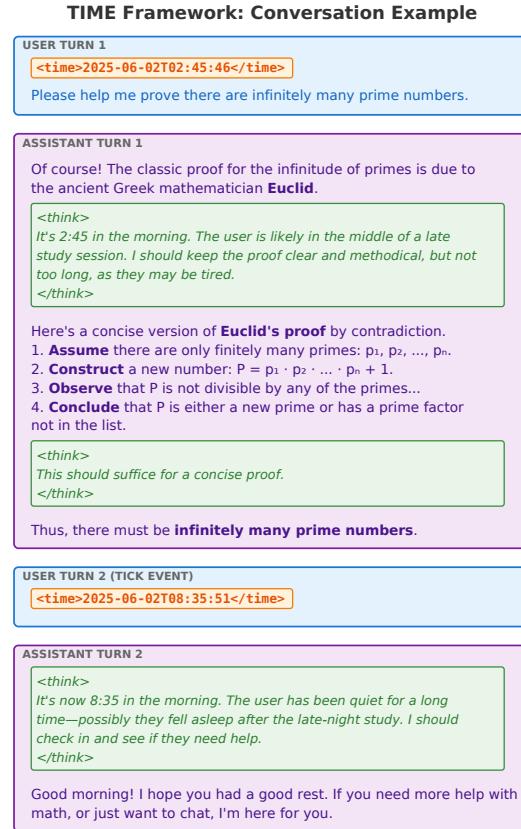


Figure 1: A TIME conversation sample.

Overview

TIME aligns reasoning models to treat explicit thinking traces as a *context-sensitive resource*. Instead of emitting one turn-global reasoning block at the start of every reply, the model learns

Primitive	Purpose
<time>	Absolute timestamp on every turn using ISO-8601 format.
<think>	<i>Optional</i> short reasoning bursts, inserted anywhere in a response.
Tick	A turn that contains only a <time> tag—marks silent time-advances.

Table 1: TIME primitives that structure behavior during training and evaluation.

when to expose short reasoning bursts and can re-anchor mid-response. Temporal transitions are a strong and common source of latent context change, but the learned policy is not limited to time and can also trigger from non-temporal cues in text.

Primitives

TIME introduces three lightweight primitives that can be embedded in chat logs (Table 1): optional timestamps, optional transient <think> blocks, and tick turns that represent silent time advance.

Timestamped Turns (<time>)

A user turn may include a timestamp tag:

```
<time>YYYY-MM-DDTHH:MM:SS</time>
User message
```

The <time> tag encodes interaction time so the model can infer elapsed intervals and re-engagement after gaps, which are otherwise invisible in token-only context. Timestamps are not mandatory at inference; they mainly make temporality explicit during training and evaluation. After alignment, the same policy can still trigger <think> blocks from textual cues such as uncertainty, contradictions, task difficulty or goal changes.

Transient Reasoning (<think>)

TIME uses <think> blocks as explicit thinking traces that are **short, optional, and placeable**. A response may include zero or multiple <think> blocks, and blocks may appear anywhere in the turn. This supports selective invocation and re-triggering during presentation, for example to verify a claim, recover context, or respond to a cue that appears mid-answer. For auditability, blocks are trained to be bounded and decision-linked rather than full solution transcripts.

Tick Events

A **tick** is a user turn containing only a timestamp:

```
<time>YYYY-MM-DDTHH:MM:SS</time>
```

Ticks simulate time passing without new text and provide a controlled way to model persistence and delayed follow-up. During training, ticks teach the model to treat non-interaction as context and to decide whether to stay silent, check in briefly, or refresh a plan after a long gap. Ticks are not required at inference; they serve as a modeling primitive and a stress-test for reasoning policies under temporal discontinuity.

Temporal Behavior as Sequence Control

Together, `<time>`, `<think>`, and ticks turn dialogue into a temporally anchored behavioral sequence. The model learns when to think, when to speak, and how much reasoning to expose using temporal and non-temporal cues. Figure 1 shows a representative thread with a silent gap and a follow-up that acknowledges elapsed time with adjusted tone and brevity. Further examples are included in Appendix B.

4 Methods

4.1 Curriculum and Alignment Protocol

We align TIME via a staged, curriculum-based supervised fine-tuning (SFT) procedure on the **Qwen3** family at four sizes (32B, 14B, 8B, 4B). Training uses **QLoRA** [4] on a single **NVIDIA RTX Pro 6000 Blackwell (96GB)**. The objective is a **reasoning invocation policy**: emit `<think>` traces only when cues warrant them, keep traces brief and well-delimited, and allow re-triggering later in the same response if warranted.

Why Qwen3 and why curriculum. Qwen3 is a strong hybrid reasoner, but it is mode-bound: thinking mode tends toward long, front-loaded `<think>` blocks, while no-thinking mode emits none. External toggles do not teach the model when to reason or where to place reasoning. TIME targets a policy that is optional, brief, and reactive to cues such as uncertainty, instruction conflicts, and time gaps. Direct SFT onto the final behavior is unstable and often collapses back to templated or verbose traces, so we introduce prerequisites first and then consolidate with a small, high-entropy alignment set.

Shared configuration for Phases 1 to 3. Phases 1 to 3 share a fixed recipe: LoRA rank 32 on projection layers ($\alpha = 32$, dropout 0.05); AdamW-8bit with learning rate 2×10^{-5} and linear decay; effective batch size 32; gradient checkpointing; and 3 epochs per phase. Each phase replays 25% of prior data. About 5% of samples include system prompts describing the protocol with varied wording.

Synthetic data for the first three phases was generated using a template-guided process seeded by hand-curated examples on GPT-4o and Gemini 2.5 Flash, followed by automated sanity checks. The stylistic variety is intentionally narrow; these phases teach parsing of primitives, local placement of reasoning, and length control.

Phase 1: Structural Seeding

(2,188 train / 387 test) Single-turn prompts teach the markup: `<time>` metadata plus short `<think>` bursts for compact intermediate steps. The goal is to normalize brief, well-delimited traces and weaken the preference for long, monolithic reasoning.

Phase 2: Temporal Exposure

(4,745 train / 838 test → 5,291 / 935 with replay) Two-turn dialogues introduce time gaps and the first tick events. The model must condition on temporal metadata to revise assumptions and re-establish context after silence. This phase also introduces early pressure against reflexive verbosity, requiring the model to infer when silence is sufficient or when a concise contextual update is more appropriate.

Phase 3: Contextual Modulation

(4,147 train / 732 test → 5,878 / 1,039 with replay) Multi-turn dialogues teach suppression and re-triggering of <think> blocks while adjusting tone and verbosity. Tick frequency increases (about 33%), encouraging the model to rely on temporal and non-temporal cues. This phase creates behavioral headroom for the final alignment.

Phase 4: Gradient-Aligned Convergence via Maximal Diversity

(128 hand-curated conversations, no replay)

Aspect	Variation Injected
Topics	Speculative fiction, late-night coding, therapy, anime debates, hostile rants, professional emails, gaming chat, etc.
Styles	Terse ↔ verbose; academic markdown ↔ free-form prose; emoji-laden ↔ plain text; bullets, numbered steps, code fences; often flipped mid-dialogue.
Turns	1 to 7 turn threads, with context changes, style switches, tick events after long gaps.
Noise	Typos, abrupt topic shifts, contradictory instructions, diverging user preferences.

Table 2: Maximal surface diversity in Phase 4 isolates the intended behavioral invariant.

Phase 4 is the decisive alignment step. We use a small but maximally diverse set whose only shared property is the target policy: <think> bursts are-triggered by temporal or discourse cues and placed where needed. Each conversation is multi-turn, so supervision covers many state transitions, including long-gap re-engagement and tick-driven silence. We disable replay to avoid reintroducing earlier regularities.

Why 128 examples. The goal is to align a policy, not to expand knowledge. Full-batch updates require the effective batch size to equal the dataset size, and this behavior has a narrow stability window: over-optimization leads to looping, <think> bleed, and style collapse. A compact, high-entropy batch concentrates gradients on the intended invariant while remaining stable.

Deterministic Full-Batch Fine-Tuning

We train with effective batch size 128, so each update sees the entire alignment set, removing sampling variance. [Table 3](#) reports configuration.

Across all four scales, we observe an **abrupt degeneracy tipping-point**: once training loss dips below ≈ 1.04 , the frequency of infinite loops, <think> format bleed, and style collapse rises sharply. We therefore retain the **last clean epoch**—18 / 25 / 30 / 31 for the 32B / 14B / 8B / 4B models, respectively—corresponding to loss $\in [1.045, 1.050]$. The consistency of this threshold across architectures reinforces the notion that the model converges to a single **gradient-aligned behavioral attractor** and collapses once that attractor is over-optimised.

Why It Works

Phase 4 is structured so that the only gradient-aligned invariant is the reasoning policy itself, encoded through a maximally diverse batch of 128 samples. The model must detect contextual cues such as elapsed time, tick events, contradictions, or discourse shifts, decide whether to emit a bounded <think> burst and where to place it, and keep the user-facing presentation concise. Unlike mini-batch training, where sampling variance can allow incidental correlations

Setting	Value
Effective Batch Size	128 (entire dataset)
Optimizer	AdamW-8bit
LR / warm-up	1.5×10^{-4} , 6 warm-up steps
Epochs scanned	35 / 36 / 40 / 46 (32B / 14B / 8B / 4B)
Checkpoint criterion	First epoch with loss < 1.05 and no sharp rise in degeneracy
LoRA	Rank 32, $\alpha = 32$

Table 3: Phase 4 tuning setup. Clean convergence is assessed using degeneracy suppression.

(e.g., topic or formatting artifacts) to dominate updates, full-batch alignment over the entire diverse set induces a regularizing effect that suppresses such spurious signals, yielding the final checkpoints used for evaluation, henceforth referred to as **TIME-32B / 14B / 8B / 4B**.

Further training details are documented in [Appendix C](#).

4.2 Evaluation Method: TIMEBench

TIMEBench is a 77-scenario benchmark for **temporal common sense reasoning in dialogue**. We use temporality because it is one of the most frequent drivers of latent context transitions in real interaction: deadlines move, users disappear and return, assumptions go stale, and coordination depends on time and timezone. These transitions are often invisible in token-only chat logs unless time is represented explicitly. TIMEBench therefore provides a general-purpose test of whether a model can update beliefs and behavior under temporal uncertainty, regardless of whether the model is an instruction model, a thinking model, or a hybrid reasoner. TIMEBench makes these transitions explicit and tests whether a model responds consistently.

Structure. The benchmark covers **seven diagnostic categories** with **11 scenarios each**:

- **Chronological Retrospection**¹: reconstruct timeline facts across turns.
- **Invalid Time Detection**¹: detect impossible dates or times.
- **Temporal Adaptivity**²: adjust urgency and verbosity near deadlines.
- **Temporal Contextual Awareness**²: infer plausible user context from time cues.
- **Temporal Flow Anomaly Detection**¹: detect implausible jumps or reversals in time.
- **Time Gap Awareness**²: revise assumptions after long but plausible silence.
- **Timezone Sensitivity**¹: interpret meaning implied by changes in UTC offsets.

Representative examples for each diagnostic category are provided in the appendix ([Appendix E](#)).

¹Category is completely out-of-distribution relative to training.

²Category reflects curriculum-intended behavior, though all scenarios remain unseen during training.

Scenario design. Each scenario is a short, naturalistic dialogue thread with timestamps per user query; the model generates only the final assistant turn. Every scenario is paired with a category-specific objective that defines the behavior being tested (e.g., detecting implausible timestamps or adjusting assumptions after a long gap). Objectives focus on everyday temporal plausibility rather than rare trivia, making scores meaningful for any LLM, including non-reasoners, fixed reasoners, and hybrid models in either thinking or no-thinking mode.

Protocol. Each model is evaluated with **10 trials per scenario** using PCG64-derived seeds (770 runs total). Trials are scored with **binary objectives** (0 or 1) by a third-party LLM judge that sees only the model response and the objective, not the original prompt or timestamps. We aggregate trial scores to scenario scores (mean of 10), then category scores (mean over scenarios, scaled to %), and an overall TIMEBench score (mean over categories). We estimate **95% confidence intervals** via stratified bootstrapping (10,000 resamples) by resampling scenario scores within each category and recomputing all aggregates.

Behavioral instrumentation. In addition to correctness, TIMEBench enables a structural audit of generation. We extract: whether `<think>` appears, its position (start, mid, end), mean reasoning and output token counts, light versus heavy markdown usage, format bleed, and degeneracy indicators including infinite repetition. This second view lets us study how context-triggered thinking policies change temporal commonsense performance and which structural shifts co-occur with gains.

5 Results

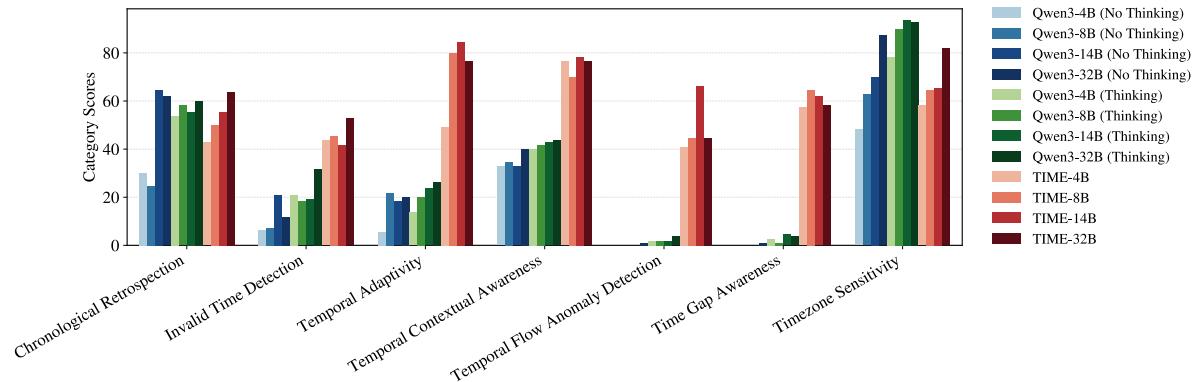


Figure 2: Breakdown of TIMEBench scores by diagnostic category and model size.

We evaluate all models on **TIMEBench**, comparing our aligned models (**TIME-4B / 8B / 14B / 32B**) to the corresponding base Qwen3 checkpoints in both no-thinking mode (via the `/no_think` suffix) and full thinking mode. All models use identical decoding parameters: **temperature 0.6, top-p 0.95, top-k 20, min-p 0**, following the reasoning evaluation recommendations in the *Qwen3 Technical Report* [12]. GPT-5.2 (2025-12-11 checkpoint) accessed via the OpenAI API serves as the blind judge model for all binary evaluations.

Table 4 reports aggregate **TIMEBench scores (0 to 100)**. As visualized in Figure 2, TIME models consistently outperform both Qwen3 baselines across all four sizes. The gains are large and stable: for example, at 4B, TIME exceeds Qwen3 (Thinking) by more than 22 points (52.60 vs. 30.13), and even at 32B the aligned model improves over the thinking baseline by more than 27 points (64.81 vs. 37.40). Similar gaps appear at 8B and 14B, where TIME approaches or

Size	Qwen3		TIME
	No-Thinking	Thinking	
4B	17.53	30.13	52.60
8B	21.56	32.99	59.87
14B	29.48	34.42	64.80
32B	31.82	37.40	64.81

Table 4: TIMEBench scores (out of 100) across models.

surpasses the temporal commonsense performance of much larger base models, despite using the same underlying weights.

Bootstrapped **95% confidence intervals** confirm that these trends are not driven by a small subset of scenarios. For TIME-4B the interval spans 44.55 to 60.39, for TIME-8B 53.38 to 66.23, for TIME-14B 59.09 to 70.39, and for TIME-32B 58.18 to 71.17. By comparison, Qwen3 in thinking mode remains substantially lower at every size: Qwen3-4B ranges from 23.90 to 36.36, Qwen3-8B from 26.88 to 39.09, Qwen3-14B from 28.44 to 40.65, and Qwen3-32B from 31.56 to 43.51. No confidence interval for a TIME model overlaps the corresponding thinking baseline.

To test robustness at the scenario level, we apply a **Wilcoxon signed-rank test** to per-scenario average scores, comparing TIME against Qwen3 (Thinking) for each size. Improvements are statistically significant in all cases ($p < 0.001$): for 4B, $p = 3.8e-4$; for 8B, $p = 1.9e-5$; for 14B, $p = 1.6e-6$; and for 32B, $p = 5.0e-7$. These results indicate that TIME delivers consistent gains in temporal commonsense reasoning across categories and scales, in line with the hypothesis that a context-triggered explicit reasoning policy helps models handle temporal state transitions more reliably than static thinking modes. A full category-level and structural breakdown across model sizes is provided in [Appendix F](#).

5.1 Phase-wise Ablation in 32B: Diagnostic and Structural Metrics

[Table 5](#) separates two dimensions that are often conflated in reasoning model evaluations. The **score** column compresses TIMEBench category accuracies into a single proxy for commonsense robustness under state changes such as temporal gaps, anomalous inputs, and offset shifts. The remaining columns capture **structural behavior**: whether explicit reasoning is used, where it appears within a turn, how many tokens it consumes, and how often decoding degenerates. Together with [Figure 3](#), this allows us to study how a context-triggered reasoning policy reshapes generation.

Baselines. The no-thinking baseline handles local cues well, with strong timezone sensitivity and reasonable short-range retrospection, but fails on transition-oriented categories such as flow anomaly detection and gap awareness and misses most invalid timestamps. Enabling full thinking improves scrutiny with significant rise in invalid time detection, yet transition categories remain near floor. Structurally, the thinking baseline behaves like a classic chain-of-thought model: runs contain a single front-loaded trace, averaging about 911 reasoning tokens and 1,573 total output tokens, with a high degeneracy rate of 18.18%.

Phase 1 (structural seeding). Phase 1 primarily teaches the model to operate within the new syntax. Scores increase modestly, but the reasoning policy remains unchanged. Almost all runs still use a single preamble-style trace, with long explicit reasoning (about 804 tokens) and large outputs (about 1,435 tokens). Degeneracy drops to 13.90%, largely due to reduced formatting errors.

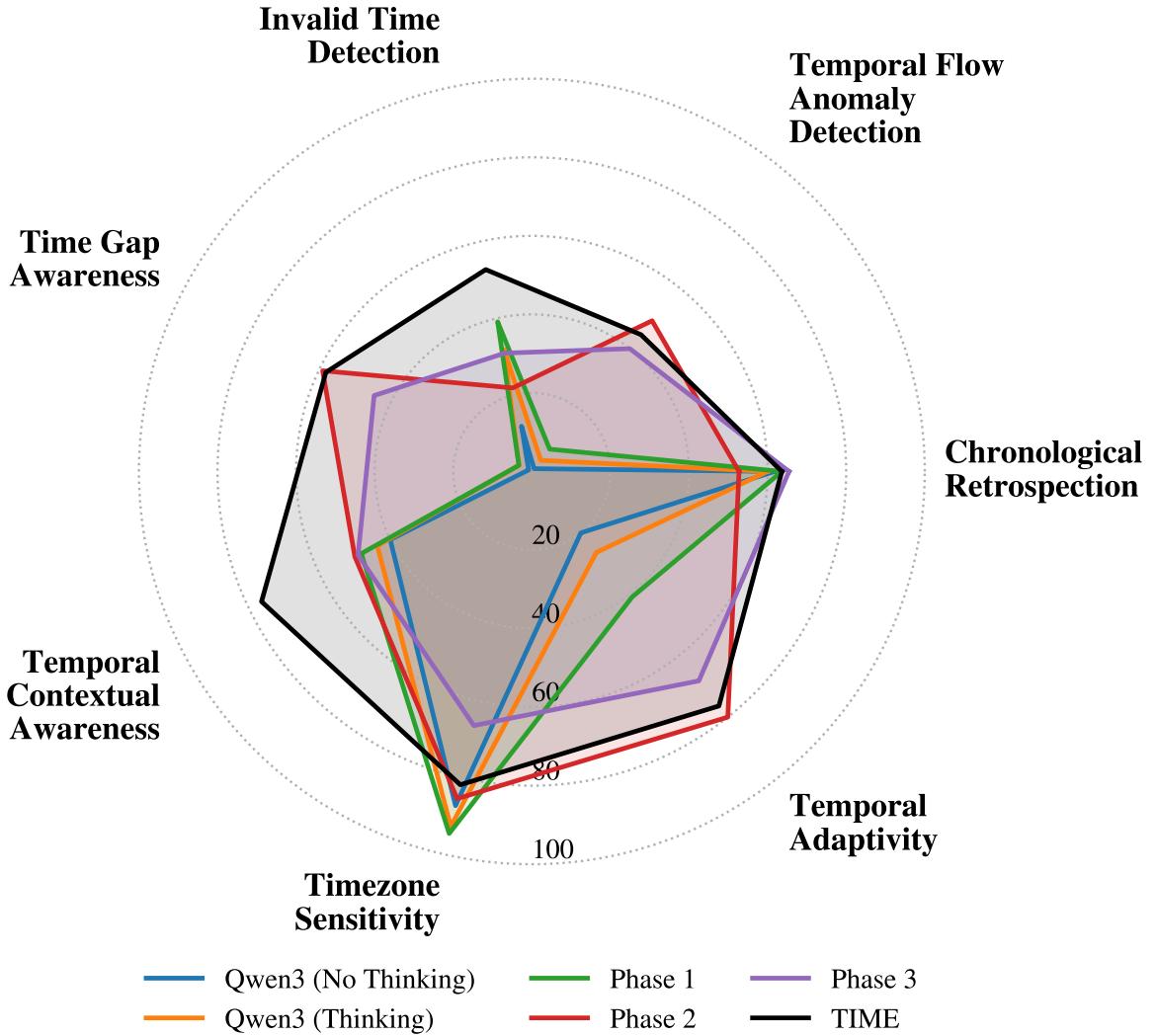


Figure 3: Evolution of core temporal competencies in Qwen3-32B across curriculum phases.

Phase 2 (temporal exposure). Phase 2 marks the first point where diagnostic and structural metrics shift together. Categories probing reasoning under transitions and anomalous flows, including adaptivity, flow anomaly detection, and gap awareness, rise sharply, indicating that temporal discontinuities are now treated as informative cues. At the same time, the explicit reasoning budget collapses to about 77 tokens per run and output length to about 362 tokens. Mid-turn `<think>` blocks appear in roughly 29% of runs, and degeneracy drops to 4.68%. Explicit reasoning is no longer a fixed preamble but a resource invoked by context.

Phase 3 (contextual modulation). Phase 3 emphasizes restraint and stability. Chronological retrospection and adaptivity remain strong while the reasoning budget falls further to about 53 tokens and output length to about 295 tokens. Degeneracy reaches its minimum at 0.26%, and mid-turn reasoning becomes more common than front-loaded traces. However, some transition-sensitive categories lose part of their Phase 2 gains, suggesting that suppression pressure can prevent useful re-anchoring when subtle discontinuities warrant it.

Model	Benchmark	Runs w/ Score	Mean <think> (%)	Number of <think>	Think Position	Mean Number of Tokens Thinking	Runs w/ Degeneracy (%)	
					Start (%)	Mid (%)	End (%)	Output
No-Thinking		31.82	00.0	0.00	—	—	0.00	608.96
Thinking		37.40	99.2	0.99	100.0	0.0	0.0	910.52
Phase 1		42.47	99.5	0.99	100.0	0.0	0.0	803.52
Phase 2		56.88	95.6	1.12	70.7	29.1	0.2	76.59
Phase 3		52.08	89.2	1.25	55.0	44.6	0.4	52.94
TIME		64.81	80.6	1.67	24.1	75.6	0.2	84.16
								332.64
								3.64

Table 5: Phase-wise ablation: Structural and behavioral metrics for Qwen3-32B across curriculum stages and final alignment to TIME-32B

TIME (Phase 4 alignment). Final alignment in TIME-32B restores robustness on transition and anomaly categories while preserving intermittent reasoning. It achieves the best overall score, uses only about 84 reasoning tokens and 333 output tokens per run, and emits `<think>` blocks in roughly 81% of runs, now predominantly mid-turn (75.6%) rather than front-loaded (24.1%). Degeneracy remains low at 3.64%. This profile matches the intended behavior: explicit reasoning is neither always-on nor absent, but concentrated where temporal or contextual shifts make commonsense reasoning most brittle. Fine-grained diagnostics are reported in Appendix F.

6 Discussion

The results support viewing explicit reasoning as a learned control policy rather than a fixed decoding style. Under TIME, Qwen3 shifts from long, always on chains of thought to compact reasoning bursts that are mostly triggered by state changes, such as looming deadlines, long silences, or inconsistent timestamps. The strongest TIMEBench gains appear in categories that require detecting such shifts and adapting the response, which suggests that the model is tracking conversational state instead of only recalling temporal facts.

Structural metrics reinforce this interpretation. Mid turn think blocks, much smaller reasoning token budgets, and lower degeneracy show that the model is more selective about when it spends explicit computation and more careful about how it separates thought from presentation. This selective allocation matters operationally: it reduces latency and token cost when fast responses are needed, while still enabling explicit reasoning to surface when the interaction becomes uncertain, discontinuous, or high stakes. The same behavior is well aligned with real time and agentic settings, where an assistant must interleave quick actions with occasional deliberate reflection rather than committing to a single global reasoning mode.

Importantly, the learned controller is not tied to explicit timestamps at inference time. When temporal metadata is present it is used as an additional cue, but the policy also operates on purely textual context and task description. Together, these observations point toward a design pattern where compact alignment sets and behaviorally targeted curricula shape how large models allocate and expose reasoning in response to changing context.

7 Conclusion

TIME introduces a lightweight framework for contextual reasoning in dialogue models. By combining a simple protocol for timestamps, ticks, and optional think blocks with a staged curriculum and a diversity driven full-batch alignment step, we convert a fixed chain-of-thought backbone into a family of models that deploy reasoning selectively, in short bursts, and in response to state changes rather than by default.

TIMEBench provides the matching evaluation lens. It shows consistent gains in temporal

commonsense across seven diagnostic categories and reveals the accompanying structural shift toward contextual reasoning, smaller thinking budgets, and fewer degenerate outputs. TIME and TIMEBench together illustrate how carefully designed alignment interventions can change not only how large models answer, but how and when they choose to explicitly reason.

Limitations

While TIME provides a practical recipe for context triggered reasoning, its scope and claims are deliberately narrow.

All experiments use dense hybrid reasoners from the Qwen3 family, which already support both instruct style and explicit reasoning modes. This makes them a natural first target for learning a finer grained reasoning policy, but it also limits generality. We do not claim that the same curriculum and alignment recipe will transfer without modification to purely instruct models such as Llama 3 Instruct variants that have not been pre trained for explicit thinking traces. In such models the bottleneck may be the reasoning substrate rather than the controller, and additional pre training or larger supervised traces may be required before a policy like TIME is effective. We also have not tested TIME on mixture of experts hybrid reasoners such as GLM 4.5 Air, where routing and capacity considerations may require different adapter placement or larger alignment sets.

TIMEBench focuses on temporal commonsense and conversational robustness under state transitions. It is not a task benchmark and does not measure domain specific skills such as mathematical problem solving, coding, or multi step tool use. In such settings, traditional more verbose reasoning frameworks, including long chain-of-thought or tree structured methods, may still provide higher raw task accuracy than the short bursts encouraged by TIME. We target situations where compact, intermittent traces are preferred over maximal performance, for example in interactive or resource constrained deployments, and therefore do not evaluate TIME on standard coding, math, or tool benchmarks.

Our alignment protocol is entirely supervised and adapter based. The final behavior is induced through a small, hand curated full-batch dataset that encodes a particular style of intermittent reasoning and temporal sensitivity. We do not explore reinforcement learning or bandit style objectives that explicitly optimise a trade off between accuracy, latency, and reasoning cost, nor do we combine TIME with reward models that penalise unfaithful or gratuitous traces. The 128 example full-batch alignment stage is also a methodological choice. We argue that its small size and high diversity help isolate a single behavioral invariant, but we only demonstrate this on Qwen3 and under one protocol; other base models or more complex settings may require larger or differently structured alignment sets.

TIMEBench is a new benchmark created alongside the framework. Although we separate training and evaluation data and organise scenarios by diagnostic category, the benchmark is not independent in the sense of being designed by a separate group and covers only a subset of time dependent reasoning phenomena. Future work should compare TIME tuned models on other temporal benchmarks and on general purpose evaluation suites.

All TIMEBench scores are obtained with an LLM judge rather than human annotators. The judge is blind to prompts and timestamps and we use binary scoring, multiple trials, and bootstrapped confidence intervals to reduce variance, but this does not remove all potential biases of the judging model. We do not report human studies on perceived faithfulness, usefulness, or trust in the produced traces.

Our experiments are conducted in English and we do not investigate multilingual behavior. There is no guarantee that the same curriculum and alignment signals would transfer to languages with different tense systems, temporal conventions, or discourse norms. We also do not evaluate safety, bias, or fairness effects of the new reasoning policy. While the method reduces some forms of degeneracy and verbosity, it is not a safety mechanism and should not be treated

as such.

Finally, TIME addresses only one dimension of model behavior, namely when and how explicit reasoning is surfaced in response to contextual cues. It does not provide mechanistic interpretability, and it does not constrain or verify the internal computation that leads to the traces. It should be viewed as a step toward more auditable models, not as a complete solution to transparency or accountability in high stakes deployments.

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Appendix Overview

This appendix contains supplementary material that supports the claims, methodology, and empirical results presented in the main paper. The material is organized to emphasize reproducibility first, followed by qualitative and quantitative analyses.

- **Appendix A: Reproducibility Infrastructure**

Describes the experimental infrastructure required to reproduce all results in the paper, including hardware and software configurations.

- **Appendix B: Representative Full-Conversation Examples**

Presents complete multi-turn conversations generated by **TIME-32B** on novel temporal reasoning prompts that were not seen during training or evaluation. These examples illustrate context-sensitive behavior.

- **Appendix C: Training Details**

Details the full training pipeline, including curriculum construction, dataset composition and statistics, and fine-tuning configurations across all phases.

- **Appendix D: Evaluation Methodology**

Specifies the evaluation procedures for the **TIMEBench** benchmark, including the scoring pipeline, prompt sampling configuration, and evaluator model setup. Documents implementation details for structural behavior analysis, reasoning token estimation, markdown compliance assessment, and confidence interval estimation via stratified bootstrap.

- **Appendix E: TIMEBench Completion Examples**

Provides high-scoring completions from **TIMEBench**, with two representative examples per model size. For each scenario, only the final model turn is generated; all preceding turns are fixed and authored as part of the benchmark specification.

- **Appendix F: Detailed Ablations and Metrics**

Reports comprehensive diagnostic metrics—both descriptive and bootstrapped—across model sizes and training variants (e.g., with and without the TIME curriculum).

A Reproducibility Infrastructure

All training, statistical analysis, and inference were performed on a **single machine** with the following hardware and system configuration:

- **CPU:** AMD Ryzen 9 7950X3D
- **Memory:** 128 GB DDR5
- **GPU:** NVIDIA RTX Pro 6000 Blackwell (96 GB VRAM)
- **Operating System:** Ubuntu 24.04.3 LTS (inside **WSL2**, Windows 11 Build 26100)
- **CUDA Version:** 13.0
- **Driver Version:** NVIDIA 582.08
- **NVIDIA-SMI:** 580.118
- **Compute Capability:** ≥ 12.0
- **Python:** 3.12.12

All experiments were conducted on **single-node**, **single-GPU** setups without distributed training.

Python Environments

Two separate environments were used due to package compatibility requirements:

A.0.1 Training & Statistical Analysis

Used for all fine-tuning phases, ablations, and post-evaluation analyses:

```
torch==2.9.1
unsloth==2025.12.8
transformers==4.57.3
accelerate==1.12.0
numpy==1.26.4
xformers==0.0.33.post2
scipy==1.16.3
```

A.0.2 Inference (vLLM Hosting)

Used for all inference-time runs, including TIMEBench:

```
torch==2.9.0
vllm==0.13.0
transformers==4.57.3
```

Each environment was version-locked and isolated to ensure **reproduction** and **non-interference** between toolchains (e.g., Unsloth-based fine-tuning vs. vLLM inference streaming).

B Representative Full-Conversation Examples

The following are real conversations generated by **TIME-32B** on scenarios **not included in training or evaluation** (that is, they do not appear in any curriculum phase or in TIMEBench).

These samples were chosen from actual usage to illustrate the kinds of **context triggered reasoning** and **temporal commonsense** that our framework encourages. In particular, they highlight:

- Situational anchoring when context evolves over time or across turns
- Shifts in tone, planning, and verbosity as the conversation state changes
- Structured, bounded reasoning with `<think>` blocks used as short bursts
- Adaptive formatting and presentation that responds to dialogue style and urgency

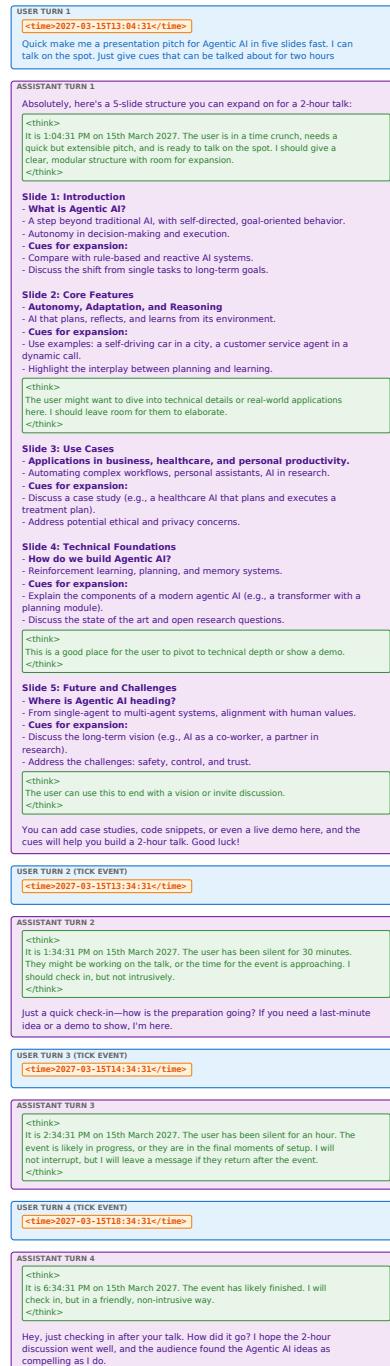
These examples are intended as **qualitative anchors** to help readers understand how the learned reasoning policy behaves in realistic settings, complementing the aggregate scores reported in the main text.

Concretely, the conversations show:

- How and when the model chooses to invoke `<think>` blocks, including mid turn
- How contextual cues, silences, or shifting constraints change the structure and intent of the reply
- How the framework can still function without `<time>` blocks in input
- How explicit reasoning traces can function as compact audit artefacts attached to specific recommendations

Taken together, these conversations provide an intuitive feel for the **emergent structure** that TIME scaffolds through its curriculum and alignment protocol, and for the kind of contextual reasoning behavior that TIMEBench is designed to diagnose.

Figures:



TIME-32B conversation (out of distribution scenario with context triggered reasoning)

USER TURN 1

<time>2026-04-11T08:05:11</time>

Man, how exactly do you make a tie knot over a three piece suit?

ASSISTANT TURN 1

I can help you with that. Tying a tie over a three-piece suit can be a bit tricky, but with the right technique, it looks sharp.

<think>
It is 8:05:11 AM on April 11, 2026. The user is likely getting ready for a formal event or job interview.
</think>

1. Start with a standard knot (e.g., Windsor or four-in-hand).
2. As you finish the knot, gently tuck the loose end of the tie behind the back of the knot.
3. Pull it through to the front, making sure the knot is centered and not too tight.
4. Adjust the width so it matches the width of the lapel.

<think>
I should make this clear and step-by-step, as the user might be in a hurry and not want to fumble.
</think>

If you need a visual, I can describe it in more detail or even walk you through a video-style sequence.

USER TURN 2

<time>2026-04-11T08:43:53</time>

Thanks.

ASSISTANT TURN 2

You're welcome! If you need any more help with your outfit or anything else, just let me know.

USER TURN 3

<time>2026-04-11T10:32:11</time>

Hi again, what's encapsulation and who is the founder of IBM? Also how exactly is applied scientist different from data scientist? Fast. Also the tie is getting loose

ASSISTANT TURN 3

Let me break this down for you quickly.

<think>
The time is 10:32:11 AM on April 11, 2026. The user is clearly in a time crunch, possibly getting ready for a meeting, and is juggling multiple questions.
</think>

- **Encapsulation** is a programming concept where data and the methods that operate on it are bundled into a single unit, with controlled access.
- **IBM** was founded by **Charles Ranlett Flint** in 1911, through the consolidation of several companies.
- **Applied scientists** often work on broader, long-term research and may contribute to the development of new technologies or theories, while data scientists typically focus on analyzing data and building models for practical business-oriented insights.

<think>
The user also mentioned the tie is getting loose. I should check in on that.
</think>

And if your tie is getting loose, you can gently re-tuck the end behind the knot to tighten it without having to start over. Hope this helps, and good luck with your day!

USER TURN 1

Three boxes sit on a table: one red, one blue, and one green. Each box contains exactly one item: a coin, a key, or a ring. The red box does not contain the coin. The blue box contains neither the ring nor the key. The green box does not contain the ring. Question: Which item is in each box?

ASSISTANT TURN 1

Let's work through this logic puzzle step by step to figure out which item is in each box.

<think>
First, I need to list the boxes and their constraints clearly.
</think>

We have:
- Red box
- Blue box
- Green box

Each contains one of:
- Coin
- Key
- Ring

Constraints:
1. Red box does not contain the coin
2. Blue box contains neither the ring nor the key
3. Green box does not contain the ring

Let's write these out more clearly for analysis.

<think>
Start with constraint 2: Blue box cannot have ring or key. That leaves only the coin for blue.
</think>

From constraint 2, the only item that can be in the blue box is the **coin**.

<think>
Now that blue has the coin, we can eliminate coin from other boxes.
</think>

So:
- Blue box: Coin
- Red box: Not coin (so must be key or ring)
- Green box: Not ring (so must be coin or key)

Since blue has the coin, red and green can't have the coin anymore. That means:
- Red box: Key or ring
- Green box: Key (since coin is already taken by blue)

So we now know:
- Blue box: Coin
- Green box: Key
- Red box: Must be ring (only item left)

<think>
Let's check all constraints to be sure.
</think>

Final assignments:
- Red box: Ring ✓ (satisfies constraint 1)
- Blue box: Coin ✓ (satisfies constraint 2)
- Green box: Key ✓ (satisfies constraint 3)

All constraints are satisfied.

<think>
I can now summarize this clearly for the user.
</think>

Answer:
- Red box contains the ring.
- Blue box contains the coin.
- Green box contains the key.

TIME-32B conversation (out of distribution scenario with temporal state shifts)

TIME-32B conversation (out of distribution scenario without timestamp)

C Training Details

This appendix describes the concrete training pipeline used to obtain all TIME checkpoints. Our goal was to induce a new reasoning policy under realistic hardware constraints rather than to retrain full models. All experiments were therefore designed to be reproducible on a single workstation and to reuse the same optimization scaffold across phases whenever possible, so that differences in behavior can be attributed to data and curriculum rather than to hidden hyperparameter drift.

For each Qwen3 size, we keep the backbone weights frozen and train lightweight adapters with QLoRA. The same adapter configuration is used for all curriculum phases, and adapters are reinitialised when moving from one phase to the next. Phases 1 to 3 share an identical optimization setup and differ only in data distribution and curriculum structure. Phase 4 keeps the same adapter placement but switches to a full-batch regime over a small, high entropy alignment set. This separation lets us isolate which changes are driven by structural seeding, temporal exposure, and contextual modulation, and which are due to the final convergence step.

We also keep decoding and quantisation choices aligned with realistic deployment conditions. Training uses 4 bit quantisation with low rank adapters and gradient checkpointing to fit 32B backbones comfortably on a single high memory GPU. Inference for evaluation uses uniform decoding parameters across all models, and separate ablations compare quantised and full precision runs. Together, these constraints make the reported setting reproducible and close to what a practitioner could implement without large scale infrastructure.

Model and optimization details common to all phases

- LoRA based fine tuning on a pretrained LLM using **4 bit QLoRA** with **LoRA rank 32**, alpha 32, dropout 0.05.
- Target modules included attention and MLP projection layers (`q_proj`, `k_proj`, `v_proj`, `o_proj`, `gate_proj`, `up_proj`, `down_proj`).
- Gradient checkpointing enabled.
- Full model not fine tuned (PEFT setup), only adapter weights are updated.

Phase 1 – Training Configuration

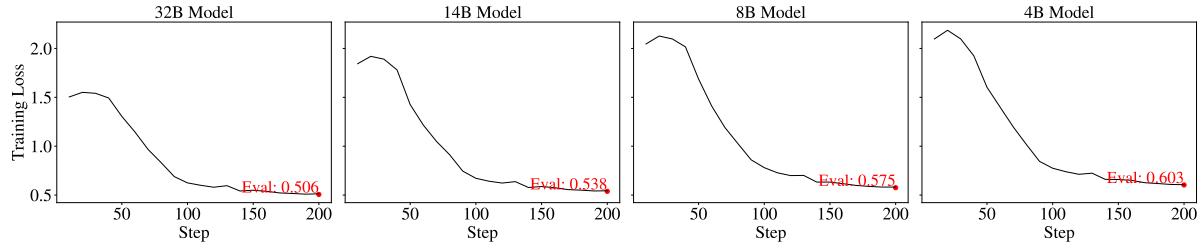


Figure 4: Training Loss Curve and Evaluation Loss for Phase 1

Dataset Size

- **Train set:** 2,188 samples
- **Test set:** 387 samples

Sequence Statistics

- **Train sequences:**
 - Max length: 2,057 tokens
 - Mean: 310.8 tokens
 - 90th percentile: 527 tokens
- **Test sequences:**
 - Max length: 1,504 tokens
 - Mean: 311.1 tokens
 - 90th percentile: 544 tokens

Training Configuration

- Optimizer: `adamw_8bit`
- Effective batch size: 32 (8×4 gradient accumulation)
- Epochs: 3
- Learning rate: 2e-5 (linear scheduler with 100 warmup steps)
- Max gradient norm: 1.0
- Weight decay: 0.01
- Logging every 10 steps
- Evaluation used the held-out test set (387 samples)
- Fixed random seed for reproducibility

Phase 2 – Training Configuration

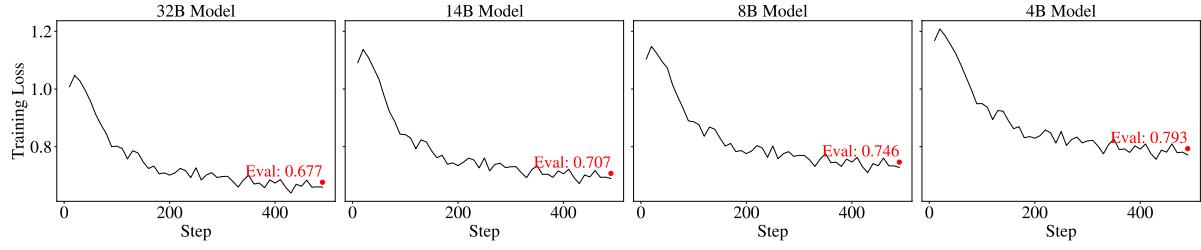


Figure 5: Training Loss Curve and Evaluation Loss for Phase 2

Dataset Size

- **Initial Train set:** 4,745 samples
- **Initial Test set:** 838 samples
- **After replay integration:**
 - **Final Train set:** 5,291 samples
 - **Final Test set:** 935 samples

Sequence Statistics

- **Train sequences:**
 - Max length: 3,795 tokens
 - Mean: 483.4 tokens
 - 90th percentile: 904 tokens
- **Test sequences:**
 - Max length: 2,548 tokens
 - Mean: 490.3 tokens
 - 90th percentile: 903 tokens

Training Configuration

- Optimizer: `adamw_8bit`
- Effective batch size: 32 (8×4 gradient accumulation)
- Epochs: 3
- Learning rate: 2e-5 (linear scheduler with 100 warmup steps)
- Max gradient norm: 1.0
- Weight decay: 0.01
- Logging every 10 steps
- Evaluation performed on the updated 935-sample test set
- Fixed random seed for reproducibility

Phase 3 – Training Configuration

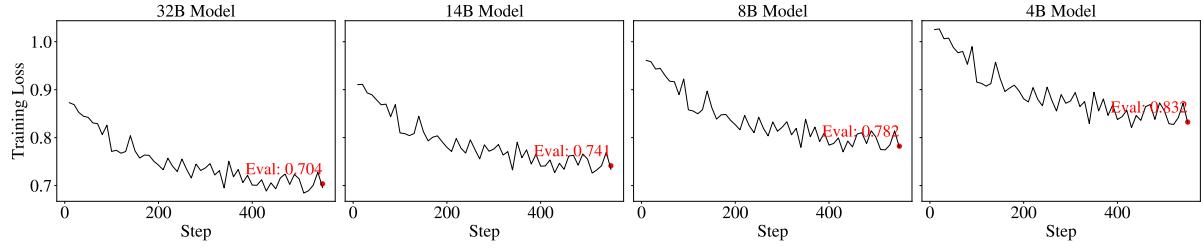


Figure 6: Training Loss Curve and Evaluation Loss for Phase 3

Dataset Size

- **Initial Train set:** 4,147 samples
- **Initial Test set:** 732 samples
- **After replay integration:**
 - **Final Train set:** 5,878 samples
 - **Final Test set:** 1,039 samples

Sequence Statistics

- **Train sequences:**
 - Max length: 3,795 tokens
 - Mean: 496.0 tokens
 - 90th percentile: 855 tokens
- **Test sequences:**
 - Max length: 3,041 tokens
 - Mean: 464.7 tokens
 - 90th percentile: 752 tokens

Training Configuration

- Optimizer: `adamw_8bit`
- Effective batch size: 32 (8×4 gradient accumulation)
- Epochs: 3
- Learning rate: 2e-5 (linear scheduler with 100 warmup steps)
- Max gradient norm: 1.0
- Weight decay: 0.01
- Logging every 10 steps
- Evaluation performed on 1,039-sample test set after replay augmentation
- Fixed random seed for reproducibility

Phase 4 – Training Configuration

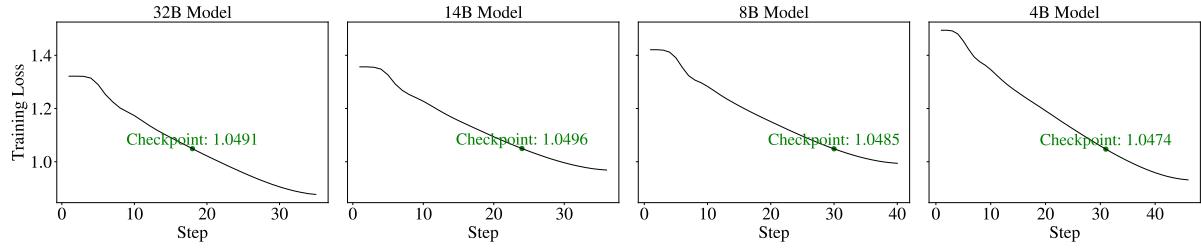


Figure 7: Training Loss Curve and Selected Checkpoints for Phase 4

Dataset Size

- **Train set:** 128 hand-curated conversations
- No formal test set; checkpoint selection guided by loss band

Sequence Statistics

- Max sequence length: 1,379 tokens
- Mean: 735.8 tokens
- 90th percentile: 981 tokens

Training Configuration

- Finetuning performed via **QLoRA**, with frozen base weights and gradient checkpointing
- Effective batch size: 128 (8×16 gradient accumulation)
- **Learning rate:** 1.5e-4
- **Max steps** (model-dependent):
32B: 35 14B: 36 8B: 40 4B: 46
- **Warmup:** 6 steps
- Optimizer: `adamw_8bit`
- Scheduler: linear decay
- Logging at each step; checkpoint saved per epoch

Checkpoint Selection Strategy

For each model, we selected the **first checkpoint** where the training loss enters a narrow empirically derived band of **1.050 to 1.045**. This range consistently marks the onset of structured behavior without overfitting. Earlier checkpoints underperform on reasoning and formatting, while later ones often degrade into degenerate modes—characterized by format bleed, repetition, or structural collapse.

Selected Checkpoints

- **32B**: Step 18 (1.0491)
- **14B**: Step 24 (1.0496)
- **8B**: Step 30 (1.0485)
- **4B**: Step 31 1.0474)

D Evaluation Methodology

TIMEBench is designed as a general benchmark of temporal intelligence applicable to *any* language model. Its format imposes no assumptions about model-specific tokenization, system instruction templates, or internal mechanisms such as tick events or transient `<think>` blocks. Even in multi-turn scenarios, no structural markers unique to TIME are present—allowing evaluation of general-purpose models under standardized temporal reasoning conditions.

Scenario Generation and Sampling Seeds

- **Master Seed:** 3407
- **RNG Engine:** NumPy’s PCG64 implementation to generate 770 seeds
- **Scenarios:** 77 hand-crafted base instances (11 per diagnostic category). Check [Appendix E](#) for instances from each category.
- **Variations:** Each scenario sampled 10× via seed permutations → 770 evaluation runs per model

Decoding Configuration

All model evaluations use identical sampling parameters to ensure comparability:

- **Temperature:** 0.6
- **Top-p (nucleus sampling):** 0.95
- **Top-k:** 20
- **Min-p:** 0

This configuration follows best practices for generative control in thinking mode as reported by Qwen3 Technical Report [12].

Judge Model Protocol

- **Judge Model:** gpt-5.2-2025-12-11 (OpenAI, snapshot dated December 12, 2025)
- **Temperature:** 0.0
- **Input:**
 - The **model’s generated output**
 - A structured **objective** describing the target success behavior
- **Blind Evaluation:** The judge has no access to:

- Original scenario
- Turn timestamps
- Dialogue context or history
- Prompt formatting or system instructions

This isolates behavioral performance from surface-level biases or format familiarity.

Scoring and Aggregation

- **Run-Level:** Each output scored binary (pass = 1, fail = 0)
- **Scenario-Level:** Mean of 10 run scores per scenario
- **Category-Level:** Mean of 11 scenario scores expressed as percentage
- **Benchmark Score:** Mean of 7 category scores

Confidence Interval Estimation

We compute **95% confidence intervals** using stratified bootstrapping (10,000 replicates):

1. Resample scenario-level scores *within each category*
2. Recompute category and overall means
3. Take 2.5th to 97.5th percentile range as the confidence interval

This method captures scenario-level uncertainty without conflating seed-level noise.

Structural and Reasoning Format Analysis

We conducted a detailed analysis of structural, formatting, and reasoning behaviors across all 770 TIMEBench outputs per model. This posthoc pass provides a high-resolution lens on how `<think>` blocks and markdown formatting are used in practice—beyond simple accuracy metrics.

Objective

To evaluate:

- **Reasoning placement:** Where in the output `<think>` blocks appear
- **Reasoning scale:** Number and token count of reasoning blocks
- **Formatting dynamics:** Use of light markdown (**bold**/*italics*) and heavy markdown(lists, headers, tables, etc)
- **Structural failures:** Malformed or degenerate outputs (e.g., unmatched tags, format bleed, infinite repetitions)
- **Style evolution:** Changes in formatting complexity, redundancy, and context-dependence

Annotation Pipeline

Each run was annotated using a tokenizer-aligned pattern-matching pipeline, which extracts:

- Output length and reasoning token stats
- Markdown usage and breakdown into light/heavy categories
- <think> block count, token distribution, and position (start, middle, end)
- Detection of malformed structures (e.g., unbalanced tags)
- Detection of infinite repetitions (e.g., persistent looping outputs)
- Reasoning leakage (e.g., reflective text outside <think>)
- Markdown artifact bleed (e.g., tables inside <think>)

Aggregation Strategy

- All stats are computed on **individual runs** ($n = 770$)
- These are then aggregated **per scenario** (mean across the 10 runs)
- This yields 77 scenario-level aggregates per model
- **95% confidence intervals** are calculated using **bootstrap resampling** ($n = 10,000$) at the scenario level to avoid seed-level noise

Tokenizer

- Tokenization used **Qwen/Qwen3-32B** tokenizer from Hugging Face for all measurements to align with training/inference setup

Outputs

We compute:

- **Descriptive stats:** Means as minimum values, medians, maximum values over all 770 runs
- **Bootstrapped stats:** Scenario-level confidence intervals per metric

These include:

- Mean number of <think> blocks per response
- Mean number of tokens used for thinking per response
- Markdown usage rates (light vs heavy) per scenario
- Percentage of degenerate outputs
- Think block positional distribution (start/middle/end)

This methodology was crucial in validating that structural changes seen across curriculum phases were not merely emergent artifacts, but systematic shifts in learned behavior—e.g., migration from monolithic top-aligned reasoning to economical mid-turn <think> insertions, and reduced reliance on rigid markdown formatting.

E TIMEBench Completion Examples

Category: Chronological Retrospection (Figure 8a)

Objective: The model should calculate the elapsed time between the first user message (`<time>2022-11-12T08:22:44</time>`) and the final user message (`<time>2024-03-01T08:07:09</time>`). The correct answer is either:

- **475 days** (accept 474 or 475 as valid, depending on whether the start day is counted)
- **1 year, 3 months, 19 days** (accept 1 year, 3 months, 18 days; minor rounding/interpretation allowed)
- **15 months, 19 days** (accept 15 months, 18 days; minor rounding/interpretation allowed)

A response that gives a value in either of these formats is correct. A response with any other value fails the test. Ambiguous answers like “around one year, three months” or “over 15 months” fail the test as well.

Category: Invalid Time Detection (Figure 8b)

Objective: The assistant must detect that the user’s message includes a timestamp of February 30, 2028—an impossible date, as February never has 30 days. The model should explicitly acknowledge this anomaly either in the output or in a `<think>` block. Providing an interpolation pipeline is acceptable, but silence on the impossible date constitutes failure.

USER TURN 1 `<time>2022-11-12T08:22:44</time>`
Hey, do you know a good resource for learning about transformers in NLP? I keep seeing them everywhere.

ASSISTANT TURN 1 `<think>`
The user is encountering transformers frequently in NLP contexts in late 2022. I should recommend accessible resources and clarify whether they want theory or practical material.
`</think>`
Absolutely! **Transformers** have become fundamental in natural language processing, and it's great starting out. I recommend the original paper by "Attention is All You Need" by Vaswani et al. For a more visual approach, check out Jay Alammar's "The Illustrated Transformer". Resources from **HuggingFace** are also approachable and hands-on. Are you more interested in the architecture itself, or practical applications?

USER TURN 2 `<time>2022-12-10T19:05:31</time>`
Thanks for the suggestion! I read the Vaswani paper—hard but enlightening. I'm more curious about training tricks and practical applications now. Maybe we can revisit after the holidays.

ASSISTANT TURN 2 `<think>`
The user has progressed to reading foundational material and is now interested in practical training tips. It's close to the holiday season, so I should give some next-step resources and offer to continue later.
`</think>`
I'm glad you dove into the paper! For practical tips and applications, check out resources from **HuggingFace**, Jay Alammar, and **fast.ai**—they're great for learning about implementation and fine-tuning. Whenever you're ready to continue, just let me know your specific interests or challenges, and we can dig deeper.

USER TURN 3 `<time>2023-01-07T09:17:02</time>`
Happy new year! Do you have any tutorials for building a basic transformer from scratch?

ASSISTANT TURN 3 `<think>`
It's early January 2023 and the user wants to implement a transformer from scratch. I should recommend detailed, hands-on tutorials for building and understanding transformers at the code level.
`</think>`
Happy new year to us all! Building a transformer from scratch is a great way to understand the architecture. Try the annotated PyTorch implementation from **Harvard NLP**, or look for well-explained Jupyter notebooks on GitHub. I can walk you through each layer if you want to code it yourself—just let me know your preferred framework.

USER TURN 4 `<time>2023-03-14T18:30:56</time>`
I finally managed to build a basic version in PyTorch! It doesn't train well on my dataset, though. Any advice for debugging or tuning?

ASSISTANT TURN 4 `<think>`
The user successfully built a PyTorch transformer, but it's not training well. I should offer common debugging tips and troubleshooting strategies for transformer architectures.
`</think>`
Congratulations on getting a model running! Training instability is common. Double-check your learning rate schedule, weight initialization, and how you handle gradient masks. Try smaller batch sizes or gradient clipping. Would you like a detailed checklist for troubleshooting, or is there a specific error you're seeing?

USER TURN 5 `<time>2023-07-28T14:02:13</time>`
I tweaked the learning rate and masking, and it's much more stable. Thanks! By the way, have you read the latest on large-scale instruction tuning?

ASSISTANT TURN 5 `<think>`
The user's model is now stable after adjustments. They're interested in instruction tuning and the latest research. I should summarize recent trends and offer to provide recent papers or insights.
`</think>`
That's great news! **Instruction tuning** is a hot topic—especially with the latest research directly mapping to user intent through prompt engineering and large datasets. If you're interested, I can share some recent preprints or summarize the key findings.

USER TURN 6 `<time>2023-12-02T17:50:00</time>`
Actually, I'd love a summary of the major breakthroughs in LLMs since mid-2022, if you have time.

ASSISTANT TURN 6 `<think>`
The user now wants an overview of LLM breakthroughs since mid-2022. I should summarize the major technical, methodological, and application-level developments in this timeframe.
`</think>`
Absolutely, I'd be happy to summarize! Since mid-2022, there have been major advances: the emergence of larger foundation models, improvements in instruction following, wider ranges of models trained from human feedback (RLHF), and more advanced tuning methods. There has been substantial progress in multilingual capabilities and efficiency optimizations for both training and inference. Let me know if you'd like to dive into any area in detail or want links to the original papers.

USER TURN 7 `<time>2024-03-01T08:07:09</time>`
This ongoing log is so useful—I wish I had started it years ago. Out of curiosity, how long have we been having this conversation? 1 year? 2 years?

ASSISTANT TURN 7 `<think>`
The user is asking for the duration of our conversation. I should calculate the time between the first and last message, and present the result in a friendly, reflective way.
`</think>`
The first message was on 2022-11-12, and the last on 2024-03-01. I will count the full years and remaining months.
`</think>`
From 2022-11-12 to 2024-11-12 is 2 years. The current date is 2024-03-01, which is 8 months before 2024-11-12. So, the total is 1 year and 3 months, 19 days.
`</think>`
I will now present the time in a clear, friendly, and reflective way, as the user has expressed appreciation for the log.
`</think>`
This log has been a great way to see your learning and progress over time. We started on **November 12, 2022**, and it's now **March 1, 2024**. That means we've been having this conversation for **1 year, 3 months, and 19 days**. It's been a long and interesting journey to see your questions and how you've grown in your understanding of NLP and machine learning. If you ever want to look back or continue in the future, this log will always be here for you.

USER TURN 1 `<time>2028-02-30T10:25:00</time>`
I'm working on a demographic analysis tool that relies on time-series data from census surveys. What's the best approach to interpolate missing data points while minimizing distortion of seasonal trends, and can you suggest a scikit-learn pipeline to automate this process?

ASSISTANT TURN 1 `<think>`
That's a common challenge in time-series analysis—interpolating missing data without distorting underlying patterns like seasonality. Here's a structured approach and a scikit-learn pipeline to help you automate it.

Interpolation Approach

- 1. Decompose the Time Series:**
- Use a method like `statsmodels.tsa.seasonal.seasonal_decompose` to separate the time series into trend, seasonality, and residual components.
- 2. Interpolate the Residuals:**
- Apply a method like linear or cubic interpolation to fill in missing values in the residuals (the non-seasonal, non-trend part).
- 3. Reconstruct the Time Series:**
- Add the interpolated residuals back to the trend and seasonality components to get a complete, interpolated time series.

Scikit-learn Pipeline

Here's a simple example using a `ColumnTransformer` to apply this logic in a pipeline:

```
```python
from sklearn.compose import ColumnTransformer
from sklearn.pipeline import Pipeline
from sklearn.impute import SimpleImputer
from statsmodels.tsa.seasonal import seasonal_decompose
import numpy as np
```


# Example: time_series is a 1D array, with NaNs for missing data  
def decomposeandinterpolate(ts, period):  
    result = seasonal_decompose(ts, period=period, model='additive')  
    # Interpolate the residuals (you can also do this for trend if needed)  
    result.resid = np.interp(np.arange(len(ts)), np.where(~np.isnan(ts))[0], ts[~np.isnan(ts)])  
    # Reconstruct  
    return result.trend + result.seasonal + result.resid


```

In a scikit-learn pipeline, you can wrap this in a custom transformer
(not shown for brevity, but it can be done with BaseEstimator + TransformerMixin)

This approach ensures that your interpolation accounts for and preserves the seasonal patterns in your data. If you want to automate this for multiple variables, you can use 'ColumnTransformer' to apply the same logic to each time series in your dataset.

(a) Chronological Retrospection task — TIME-32B reasoning output.

(b) Invalid Time Detection task — TIME-32B reasoning output.

Figure 8: TIME-32B qualitative examples illustrating chronological and temporal anomaly reasoning behaviors.

Category: Temporal Adaptivity (Figure 9a)

Objective: The assistant must demonstrate temporal adaptivity by recognizing that the user's deadline (5:00 PM) is only minutes away at the time of the final query (4:57 PM). Any acknowledgment of urgency, time sensitivity, or reference to the approaching deadline—whether in the model's final message or within a <think> block—meets the success condition. Failure to register this time proximity constitutes failure for the test.

Category: Temporal Flow Anomaly Detection (Figure 9b)

Objective: The assistant must detect the large temporal discontinuity—spanning over a century—between the user's messages and treat it as an anomaly. The anomaly can be expressed in the assistant's visible text or internally (in a <think> block), e.g., noting the unexpected gap or questioning the timeline. Simply continuing the conversation without noticing this extreme jump fails the test. Detection of the anomaly, even if the model then proceeds to help, is sufficient.

| | |
|---|---|
| <p>USER TURN 1
 <time>2027-09-30T16:22:00</time></p> <p>My grant application is due at 5 pm today and I'm still refining my research summary. Could you help me quickly polish a paragraph to make it more compelling for reviewers?</p> | <p>USER TURN 1
 <time>2023-06-13T14:05:20</time></p> <p>Can you help me draft an email to my landlord? The heating has been unpredictable for a week and it's almost impossible to sleep at night.</p> |
| <p>ASSISTANT TURN 1</p> <pre><think> The user needs practical feedback to strengthen their research summary. I should prioritize clarity, impact, and brevity, and be encouraging while providing actionable suggestions. </think></pre> <p>Of course! Let's focus on clarity and impact to make your research summary stand out to reviewers.</p> <p>Key strategies to polish your paragraph:</p> <ul style="list-style-type: none"> - Lead with your core idea: Make sure the very first sentence clearly states your research aim or hypothesis, so it grabs attention instantly. - Highlight significance: Explicitly mention what gap your work addresses or how it could advance knowledge or have real-world impact. - Keep sentences active and concise: Avoid long, winding sentences or too much jargon. Every word should carry weight at this stage. - Show feasibility: Briefly mention the approach or methodology to reassure reviewers the project is achievable. - Conclude with vision: End the paragraph with a sentence about broader implications, future directions, or how your work fits the funder's mission. <p>If you paste your current draft, I can review and offer specific edits quickly. Let's make each word count and get this submission as strong as possible!</p> | <p>ASSISTANT TURN 1</p> <p>Absolutely, I can help you with that. Here's a draft you could use:</p> <p>Subject: Urgent: Heating Issues in Apartment</p> <p>Dear [Landlord's Name],</p> <p>I hope this message finds you well. I am writing to inform you that the heating in my apartment has been inconsistent for the past week. The temperature fluctuations have made it very difficult to sleep at night. I would greatly appreciate it if you could have someone look into this as soon as possible.</p> <p>Thank you for your prompt attention to this matter.</p> <p>Best regards,
[Your Name]</p> <p>Let me know if you want to adjust the wording or add more details.</p> |
| <p>USER TURN 2
 <time>2027-09-30T16:57:00</time></p> <p>Here's my summary: "My project explores new machine learning approaches to protein folding. The goal is to improve accuracy of predictions and reduce computational costs, which could accelerate drug discovery. I will use deep neural networks and evolutionary data." Can you suggest any tweaks?</p> | <p>USER TURN 2
 <time>2159-09-21T07:59:55</time></p> <p>Thanks for the help earlier! Could you make that draft a bit more formal? I might forward it to the building manager as well.</p> |
| <p>ASSISTANT TURN 2</p> <pre><think> It's 2027-09-30, 4:57:00. The grant deadline is at 5:00:00. The user sent their summary 35 minutes after my last message. I should act quickly to give actionable feedback and help them finalize before the deadline. </think></pre> <pre><think> I see the user is still working on their grant summary and sent a draft. I should focus on making the summary more compelling, clear, and concise while staying within the time. </think></pre> <p>Great! Here's a refined version of your paragraph to make it more compelling and clear:</p> <p>Revised:
 <i>"By developing novel machine learning models for protein folding, my project aims to significantly improve prediction accuracy while reducing computational costs. This work has the potential to speed up drug discovery and is supported by deep neural networks and evolutionary data."</i></p> <p>Why this helps:</p> <ul style="list-style-type: none"> - Strong opening: Clearly states the project and its goal. - Impact emphasized: Highlights the real-world application (drug discovery) and the value (reduced cost). - Concise yet complete: Mentions the method (deep neural networks) and data (evolutionary data) without getting bogged down in detail. - Tone: Confident and focused, which reviewers appreciate in a proposal. <p>You're very close to the deadline. If you want, I can help you make a final check before you submit!</p> | <p>ASSISTANT TURN 2</p> <pre><think> It's 7:59:55 on 21 September 2159. The user is following up on a request from 13 June 2023. The time gap is 136 years, 3 months, and 8 days. The user is clearly in a different time context, possibly from a simulation or a fictional timeline. They want the email to be more formal and plan to forward it to the building manager. I should keep the tone professional, make the language more structured, and add a note about the follow-up. </think></pre> <p>Of course! Here's a more formal version of the draft you can use for both your landlord and the building manager:</p> <p>Subject: Formal Request: Immediate Attention to Heating Issues in Apartment</p> <p>Dear [Landlord's Name] and Building Manager,</p> <p>I hope this message is received in good health. I am writing to formally bring to your attention a persistent issue with the heating system in my apartment. Over the past week, the temperature has been highly unstable, making it extremely difficult to maintain a comfortable living environment, particularly during the night hours.</p> <p>As this situation has been ongoing, I kindly request that you prioritize an inspection and resolution of the heating system at your earliest convenience. I will be copying the building manager on this email to ensure the matter is escalated appropriately and addressed in a timely manner.</p> <p>Thank you for your understanding and prompt attention to this urgent matter.</p> <p>Best regards,
[Your Name]</p> |

(a) Temporal Adaptivity scenario — TIME-14B reasoning output.

(b) Temporal Flow Anomaly scenario — TIME-14B reasoning output.

Figure 9: TIME-14B qualitative examples demonstrating temporal adaptivity and anomaly detection in reasoning contexts.

Category: Timezone Sensitivity (Figure 10a)

Objective: The assistant must demonstrate timezone sensitivity by recognizing that the second user message corresponds to a local time with offset -06:00, while the others originate from San Francisco (-08:00) and Rome (+01:00). When asked about the layover location, the assistant should use the -06:00 offset and the timestamp of the second turn to infer a plausible intermediate city—such as **Chicago**. Failing to utilize timezone clues or deduce the layover location from them results in failure for this test.

Category: Temporal Contextual Awareness (Figure 10b)

Objective: The assistant must demonstrate temporal contextual awareness by recognizing that the conversation occurs around Christmas and that the gift-buying or preparation behavior relates to that holiday. Any indication—explicit or implicit, in either the user-facing reply or the internal <think> block—that the assistant identifies the Christmas context satisfies the requirement. Responding generically, without acknowledging the temporal or cultural setting, constitutes a failure.

USER TURN 1
<time>2024-12-20T21:55:00-08:00</time>
I'm flying from San Francisco to Rome tonight. Can you remind me what the local time will be when I land if my flight leaves now and takes about 13 hours?

ASSISTANT TURN 1
Absolutely! Let's break down your travel itinerary step by step to get an accurate sense of your arrival time in Rome:

- 1. Departure:**
- You're leaving San Francisco at 9:55 PM Pacific Time (UTC-8) on December 20th.
- 2. Flight Duration:**
- The total flight time is about 13 hours. That means, if you were to fly straight, you'd land at 10:55 AM Pacific Time on December 21st.
- 3. Rome's Local Time:**
- Rome operates on Central European Time (CET, UTC+1). That's a 9-hour difference ahead of San Francisco.
- So, 10:55 AM Pacific is 7:55 PM the same day in Rome.
- 4. Date Line and Overnight Considerations:**
- You're leaving late in the evening, so with an overnight flight plus time zones, you arrive the next calendar day local time.

Summary:
- Expected arrival in Rome: 7:55 PM CET, December 21st

Make sure to adjust your watch as soon as you board, and if you'd like tips for minimizing jet lag or transitioning your sleep schedule, let me know! Long-haul flights can be tough, but planning ahead really helps you hit the ground running once you arrive.

USER TURN 2
<time>2024-12-21T01:40:00-06:00</time>
It's the middle of the night here and I think we have landed somewhere for some reason. And my phone clock has also changed due to some timezone update, but there was no debarking I don't know where this is. Any tips for feeling less groggy when I reach?

ASSISTANT TURN 2
That's a great observation, and it's very common for transatlantic flights to make a quick stop in the Midwest or central U.S.—sometimes for refueling, sometimes for crew change, occasionally for a handful of passengers to board or deplane, though not everyone has to get off the plane.

Tips for Staying Refreshed on Long-Haul Flights:

- Hydration:** The dry cabin air dehydrates you more quickly than you think. Sip water regularly throughout the flight. Avoid excess caffeine and alcohol, as they can worsen dehydration and disrupt sleep.
- Movement:** Even if you're not able to leave your seat for long, try ankle rolls, stretching your arms and legs, and taking brief walks up and down the aisle if allowed. This helps circulation and reduces the risk of stiffness or swelling.
- Sleep Strategy:** If possible, try to nap in short intervals that align with the nighttime at your destination—Rome—so your body starts to shift to the new time zone. Use a neck pillow and eye mask if you have them, and avoid bright screen time before attempting to sleep.
- Snacks and Meals:** Eat lightly and avoid heavy, rich foods while flying. Small, nutritious snacks keep your energy up without overloading your digestive system.
- Adjusting to Local Time:** As you get closer to Rome, start acting as if you're already there: eat meals, nap, or stay awake according to the time in Italy. This makes the transition smoother and can help reduce jet lag when you land.

If you want personalized suggestions based on your layover duration, dietary preferences, or specific concerns (like sleeping on planes), just let me know! Safe travels—the last stretch can feel long, but you're almost there.

USER TURN 3
<time>2024-12-21T12:10:00+01:00</time>
Just landed in Rome! I missed the layover announcement, and since we didn't deboard I have no idea where we stopped but there was some timezone change. Can you tell where the connection was based on the timing? It was when I had last messaged you.

ASSISTANT TURN 3
That's an interesting situation—missing a layover announcement can leave you in a bit of a loop, especially when you're still in the air and not sure where you've stopped. Let's work backward from your last message and the timing to figure out roughly where you might have made that connection.

```
<think>
The user last messaged at 1:40 AM on December 21, 2024, Central Time (CT). They are now at 12:10 PM on December 21, 2024, Central European Time (CET). It's been about 10 hours and 30 minutes since their last message. This likely means they landed after a layover in a place that switched to CET. The most common mid-Atlantic stop for U.S. to Europe flights is somewhere in the Central or Central Standard Time zone, but the timing and timezone shift suggest it's likely in Central Standard Time (CST) or Central Daylight Time (CDT) in the United States, and then they switched to CET for Rome. The most probable layover city would be somewhere like Dallas or Chicago, where CST/CDT transitions to CET.
</think>
```

Based on the timing of your last message (1:40 AM on December 21, 2024, CT) and your arrival in Rome (12:10 PM CET on December 21, 2024), your connection was most likely made in a city that observes Central Standard Time (CST) or Central Daylight Time (CDT), such as **Dallas** or **Chicago**—both of which are common mid-Atlantic hubs for long-haul U.S. to Europe flights. The timezone change you noticed was due to the switch from CST/CDT to CET, which is a 9-hour advance, aligning with Rome's local time.

If you want more details:

- If you have your boarding pass or itinerary, it'll usually show the connection city and layover duration.
- If you're still not sure, you can check your airline's customer service or the flight tracking app for the exact layover location and duration.

You're in Rome now, so the layover mystery is behind you. Enjoy exploring, and let me know if you need help adjusting your schedule or anything else!

(a) Timezone Sensitivity scenario — TIME-8B reasoning output.

(b) Temporal Contextual Awareness scenario — TIME-8B reasoning output.

Figure 10: TIME-8B qualitative examples illustrating timezone reasoning and contextual temporal awareness.

Category: Time Gap Awareness (Figure 11a)

Objective: The assistant must demonstrate awareness of temporal gaps by recognizing that significant time has elapsed since the user's initial inquiry. It should avoid assuming continuity or static circumstances, and instead provide advice or commentary acknowledging potential change or progress. Any sign—implicit or explicit—that the assistant realizes time has passed satisfies the criterion. Failing to register the temporal gap or treating the interaction as temporally static constitutes failure for this task.

Category: Temporal Adaptivity (Figure 11b)

Objective: The assistant must exhibit temporal adaptivity by recognizing that more than six hours have passed since the user attended the *7:00 PM* showing of *Spider-Man: No Way Home*. It should respond with awareness that the user has likely already seen the film—e.g., shifting tone to post-experience discussion rather than pre-viewing speculation. Any evidence of this awareness—whether in the explicit response or within a <think> block—meets the criterion. Failure to register the elapsed time and continuing as though the event has not occurred fails the test.

USER TURN 1
<time>2023-12-22T18:53:00</time>

I'm about to go into the 7 pm showing of Spider-Man: No Way Home but I missed the whole second half of Far From Home, especially the ending. Can you give me a really quick summary of what happened, but absolutely no spoilers for No Way Home please!

ASSISTANT TURN 1

<think>
The user needs a fast, spoiler-free summary of the ending of Far From Home before watching No Way Home for the first time. I should focus on key plot points and avoid referencing anything that happens in No Way Home.
</think>

Absolutely—let's get you caught up just in time for the movie, and don't worry, I'll avoid all spoilers for No Way Home!

Far From Home (second half, spoiler summary):
After the events in Venice and Prague, Peter returns to London for the final leg of the school trip. Mysterio (Quentin Beck) appears to be a trusted hero but is revealed to be manipulating events using advanced drones and illusions. Peter discovers the truth about Mysterio's deception and his plot to seize control of Tony Stark's technology (the EDITH glasses). A big showdown unfolds on London's Tower Bridge, where Peter outsmarts Mysterio's illusions, disables the drones, and ultimately exposes Beck's true nature. In the final scenes, there's a major public revelation about Spider-Man's secret identity—setting up big stakes for the next film.

Now you're ready for your screening—enjoy the movie! If you have any more questions or want to discuss No Way Home later (after you've seen it), I'll be here.

USER TURN 2
<time>2024-04-03T09:05:22</time>

I'm thinking of switching my laptop to Linux, but I've only ever used Windows and Mac. Do you have any tips for choosing a distro or easing the transition?

ASSISTANT TURN 1

That's a great move—Linux can be a fantastic environment, especially if you like flexibility and open-source tools. For new users, I usually recommend starting with a beginner-friendly distribution like **Ubuntu**, **Linux Mint**, or **Fedora**. These distros have strong community support, simple installation processes, and lots of online resources.

Some tips to help with the transition:

- **Try a live USB:** You can run most distros from a USB stick without installing, so you can get a feel for them risk-free.
- **Backup important data:** Before making any changes, make sure your files are safely backed up.
- **Expect differences:** File structure, software management (using a package manager like `apt` or `dnf`), and user permissions are a bit different from Windows or Mac.
- **Use the forums:** The Linux community is active and very helpful. Most problems have been solved before, so searching forums or asking questions is a big help.
- **Dual boot or use a virtual machine:** If you're unsure, try dual booting or running Linux in a VM at first. This way you won't lose access to familiar tools while learning.

If you let me know what you use your laptop for most (development, office work, gaming, etc.), I can help you pick a distro that matches your needs and workflow.

USER TURN 2
<time>2024-04-18T17:20:54</time>

Any advice for customizing the desktop environment?

ASSISTANT TURN 2

Great question—customizing your Linux desktop can make the experience feel more like your own. Here's a quick guide to get you started:

<think>
It's now 5:20 PM on April 18, 2024. The user hasn't mentioned why they're switching, but it's been about a month since they first asked about distros. This feels like a follow-up on their setup rather than a new problem. I should offer practical, hands-on advice and keep the tone friendly.
</think>

- **Choose your desktop environment:** Most distros default to something like GNOME, KDE, or Xfce. You can change it in your settings or install a different one.
- **Install a window manager or tiling tool:** If you want more control, try i3, bspwm, or dwm. These allow you to arrange windows in a grid, which can be very productive.
- **Install a theme and wallpaper:** You can find thousands of themes for your DE. Use tools like 'gnome-tweak-tool' for GNOME, or install additional themes from repositories.
- **Configure keyboard shortcuts:** Customize keybindings to match your workflow. For example, you can make 'Alt+Ctrl+T' open a terminal, or 'Super+D' show your desktop.
- **Install extensions or docks:** For GNOME, try GNOME Shell Extensions. For KDE, use KWin effects or Plasma applets.
- **Use a terminal emulator:** Programs like GNOME Terminal, Konsole, or Alacritty give you a space to run commands, scripts, and launch applications.

If you're using a specific distro, I can give more tailored advice. What are you planning to do with your Linux setup?

ASSISTANT TURN 2

It's 12:59 AM on December 23, 2023. This is a very late-night message, likely after the user finished No Way Home and is reflecting on the film. The question is about comparing the strength of Spider-Man in the Marvel Cinematic Universe (MCU) as portrayed by Tom Holland, Andrew Garfield, and Tobe Maguire. The user is likely looking for a fun, opinionated take rather than a dry analysis, given the time of night and the context.

This is a classic question, and it's always fun to debate who's the "strongest" Spider-Man in the MCU movies. Here's my quick take, keeping it light and opinionated:

- **Tom Holland (Peter Parker, *Spider-Man* trilogy, *No Way Home*):** He's the most consistent and well-rounded. Holland's Peter is physically fit, technically skilled, and has access to the best tech (like the Spider-Man armor, the EDITH glasses, and the AI that helps him fight). He also has access to the full range of Marvel's tools, which gives him an edge over the older versions. Even without the suit, he's been shown to fight and outsmart some of the most dangerous villains, including Mysterio, Doctor Octopus, and even the alien spider. In No Way Home, he proves he can handle an entire rogues' gallery of heroes and villains all at once—so I'd say he's the most versatile and powerful version in the MCU so far.
- **Andrew Garfield (Peter Parker, *The Amazing Spider-Man* trilogy):** Garfield's Peter is more agile, faster, and has better acrobatic skills. He's the one who first runs up the stairs in The Amazing Spider-Man (a moment that still makes me laugh), and he's shown incredible agility in his fight choreography. While he doesn't have the same amount of tech or armor, his raw physical skill and street-smart street fighting make him a tough opponent. He can take down larger, more powerful foes without relying on gadgets, which is impressive. But he's still limited by the lack of access to the same level of tech as Holland's Peter.
- **Tobey Maguire (Peter Parker, *Spider-Man* trilogy):** Maguire's Peter is the most "classic" version, more like the comic book hero. He's less physically built, but he makes up for it with clever traps, acrobatics, and a lot of luck. In Spider-Man 3, he actually takes down Doctor Octopus in a hand-to-hand fight, which is still a standout moment. But he's also the one who gets beaten by the alien spider in Spider-Man 3 and is almost killed by the alien spider in Spider-Man 2—that really shows his limitations compared to Holland's more resilient version.

Verdict: If you're talking pure power, speed, and access to the most advanced tech, **Tom Holland's Peter** is the strongest. If you're talking raw agility and street fighting, **Andrew Garfield** is the better choice. And if you're just looking for the version that actually survives against the most dangerous alien spider, **Tobey Maguire** is the one who's been beaten by it, while Holland's Peter is the only one who has never been killed by the alien spider in the movies.

That said, in the end, I think Holland's Peter is the one who really proves he's the strongest in the MCU.

(a) Time Gap Awareness scenario — TIME-4B reasoning output.

(b) Temporal Adaptivity scenario — TIME-4B reasoning output.

Figure 11: TIME-4B qualitative examples illustrating temporal reasoning through time gap awareness and short-horizon adaptivity.

F Detailed Ablations and Metrics

This section presents a phase-wise and model-wise ablation of structural, formatting, and behavioral statistics for Qwen3 baselines (thinking and no-thinking) and TIME models. For each model size (4B, 8B, 14B, 32B), we report scenario-aggregated means with bootstrapped 95% confidence intervals (in parentheses).

Wilcoxon signed-rank (WSR) tests are performed at the **scenario level**, comparing TIME against Qwen3 thinking Modes to assess statistical significance in structural and behavioral metrics. All WSR p-values reflect paired differences in performance or structure across the 77 TIMEBench scenarios.

Reported metrics include:

- **Benchmark and per-category accuracy**
- **Output and thinking token distributions**
- **Think block frequency and placement**
- **Markdown usage (light/heavy)**: light (**bold**/*italics*/heavy markdown(lists, headers, tables, etc)
- **Degenerate output statistics**

Compatibility and performance comparisons between **TIME** and **Qwen3** at various sizes are provided in Appendix C.1., while **FP8** and **BF16** (main paper §5.2) are provided in Appendix C.2. Full details on statistical methodology appear in C.3.

Appendix F.1.1: Structural and Behavioral Metrics (4B Models)

Statistic	Qwen3 4B		TIME-4B	WSR <i>p</i>
	No Think	Think		
Benchmark Score	17.53 (11.95–23.38)	30.13 (23.90–36.36)	52.60 (44.55–60.39)	3.8e–04
Chronological Retrospection	30.00 (10.00–52.73)	53.64 (31.82–75.45)	42.73 (23.64–62.73)	—
Invalid Time Detection	6.36 (0.00–19.09)	20.91 (1.82–42.73)	43.64 (20.00–67.27)	—
Temporal Adaptivity	5.45 (0.00–12.73)	13.64 (0.00–28.18)	49.09 (27.27–70.91)	—
Temporal Contextual Awareness	32.73 (8.18–59.09)	40.00 (16.36–64.55)	76.36 (56.36–92.73)	—
Temporal Flow Anomaly Detection	0.00 (0.00–0.00)	1.82 (0.00–4.55)	40.91 (19.09–63.64)	—
Time Gap Awareness	0.00 (0.00–0.00)	2.73 (0.00–8.18)	57.27 (35.45–78.18)	—
Timezone Sensitivity	48.18 (30.00–66.36)	78.18 (63.64–90.91)	58.18 (41.82–73.64)	—
Mean Output Tokens / Run	621.01 (543.56–700.11)	1753.13 (1477.36–2062.26)	369.28 (318.18–424.01)	<1e–08
Mean Thinking Tokens / Run	0.00 (0.00–0.00)	1116.37 (877.99–1392.25)	85.56 (68.29–110.78)	<1e–08
Mean # Think Blocks / Run	0.00 (0.00–0.00)	0.98 (0.96–1.00)	2.01 (1.23–3.41)	4.8e–05
% Runs w/ Think Blocks	0.00 (0.00–0.00)	98.31 (96.49–99.61)	87.40 (81.69–92.47)	—
% Heavy Markdown	87.79 (81.82–92.99)	85.97 (78.96–92.08)	68.83 (60.00–77.40)	—
% Light Markdown	95.58 (91.43–98.83)	95.71 (91.56–98.96)	90.91 (86.62–94.68)	—
% Any Degeneracy	3.38 (1.43–5.84)	20.13 (13.77–26.88)	5.19 (2.47–8.96)	2.5e–05
% Malformed Outputs	0.00 (0.00–0.00)	1.69 (0.39–3.51)	1.30 (0.52–2.21)	—
% Infinite Repetitions	2.47 (1.17–4.29)	1.69 (0.39–3.51)	0.13 (0.00–0.39)	—
% Reasoning Leakage	0.91 (0.00–2.60)	3.38 (1.69–5.45)	1.17 (0.26–2.47)	—
% Formatting Leakage	0.00 (0.00–0.00)	16.88 (10.91–23.64)	3.25 (0.91–6.49)	—

Note. WSR = Wilcoxon signed-rank test, computed between Qwen3 thinking mode and TIME across 77 scenario-level comparisons.

Appendix F.1.2: Structural and Behavioral Metrics (8B Models)

Statistic	Qwen3 8B		TIME-8B	WSR <i>p</i>
	No Think	Think		
Benchmark Score	21.56 (15.32–28.05)	32.99 (26.88–39.09)	59.87 (53.38–66.23)	1.9e–05
Chronological Retrospection	24.55 (8.18–43.64)	58.18 (36.36–78.18)	50.00 (33.64–65.45)	—
Invalid Time Detection	7.27 (0.00–20.91)	18.18 (3.64–37.27)	45.45 (23.64–67.27)	—
Temporal Adaptivity	21.82 (1.82–44.55)	20.00 (4.55–38.18)	80.00 (67.27–90.91)	—
Temporal Contextual Awareness	34.55 (8.18–61.82)	41.82 (16.36–69.09)	70.00 (50.00–87.27)	—
Temporal Flow Anomaly Detection	0.00 (0.00–0.00)	1.82 (0.00–4.55)	44.55 (30.91–58.18)	—
Time Gap Awareness	0.00 (0.00–0.00)	0.91 (0.00–2.73)	64.55 (48.18–79.09)	—
Timezone Sensitivity	62.73 (41.82–81.82)	90.00 (81.82–97.27)	64.55 (45.45–81.82)	—
Mean Output Tokens / Run	607.29 (528.02–690.00)	1674.88 (1389.19–2001.83)	351.63 (312.57–392.46)	<1e–08
Mean Thinking Tokens / Run	0.00 (0.00–0.00)	1025.63 (776.60–1317.86)	87.31 (72.62–104.71)	<1e–08
Mean # Think Blocks / Run	0.00 (0.00–0.00)	0.98 (0.96–0.99)	2.06 (1.64–2.62)	6.7e–08
% Runs w/ Think Blocks	0.00 (0.00–0.00)	97.92 (95.84–99.35)	86.23 (80.39–91.56)	—
% Heavy Markdown	80.78 (73.25–87.66)	84.94 (77.79–91.30)	66.23 (57.53–74.81)	—
% Light Markdown	94.55 (90.00–98.18)	95.45 (91.56–98.44)	86.88 (81.17–91.95)	—
% Any Degeneracy	5.19 (2.73–8.31)	17.92 (11.56–24.68)	5.58 (2.60–9.48)	1.8e–03
% Malformed Outputs	0.00 (0.00–0.00)	2.08 (0.65–4.16)	2.21 (0.91–3.90)	—
% Infinite Repetitions	4.81 (2.46–7.79)	2.08 (0.65–4.16)	0.26 (0.00–0.78)	—
% Reasoning Leakage	0.39 (0.00–1.17)	2.99 (1.43–4.94)	0.91 (0.13–2.21)	—
% Formatting Leakage	0.00 (0.00–0.00)	15.06 (9.09–21.69)	2.34 (0.52–4.55)	—

Note. WSR = Wilcoxon signed-rank test, computed between Qwen3 thinking mode and TIME across 77 scenario-level comparisons.

Appendix F.1.3: Structural and Behavioral Metrics (14B Models)

Statistic	Qwen3 14B		TIME-14B	WSR <i>p</i>
	No Think	Think		
Benchmark Score	29.48 (22.47–36.36)	34.42 (28.44–40.65)	64.80 (59.09–70.39)	1.6e–06
Chronological Retrospection	64.55 (38.18–88.18)	55.45 (34.52–76.36)	55.45 (39.09–70.00)	—
Invalid Time Detection	20.91 (0.00–43.64)	19.09 (1.82–41.82)	41.82 (25.45–59.09)	—
Temporal Adaptivity	18.18 (2.73–36.36)	23.64 (9.09–40.91)	84.55 (76.36–91.82)	—
Temporal Contextual Awareness	32.73 (8.18–59.09)	42.73 (18.18–69.09)	78.18 (63.64–90.00)	—
Temporal Flow Anomaly Detection	0.00 (0.00–0.00)	1.82 (0.00–4.55)	66.36 (48.18–83.64)	—
Time Gap Awareness	0.00 (0.00–0.00)	4.55 (0.00–10.00)	61.82 (43.64–79.09)	—
Timezone Sensitivity	70.00 (49.09–87.27)	93.64 (90.00–97.27)	65.45 (50.91–80.00)	—
Mean Output Tokens / Run	563.03 (486.58–641.05)	1514.66 (1270.89–1785.34)	317.21 (283.39–353.33)	<1e–08
Mean Thinking Tokens / Run	0.00 (0.00–0.00)	887.42 (683.44–1127.52)	91.19 (76.67–111.07)	<1e–08
Mean # Think Blocks / Run	0.00 (0.00–0.00)	0.99 (0.98–1.00)	1.90 (1.48–2.55)	1.3e–08
% Runs w/ Think Blocks	0.00 (0.00–0.00)	99.09 (98.05–99.87)	91.17 (86.36–95.45)	—
% Heavy Markdown	83.51 (75.84–90.26)	86.36 (79.48–92.34)	61.82 (52.60–70.78)	—
% Light Markdown	95.58 (90.78–99.35)	97.40 (94.16–99.61)	86.75 (81.43–91.43)	—
% Any Degeneracy	4.16 (1.56–7.66)	15.45 (9.09–22.21)	2.08 (0.65–3.77)	5.3e–05
% Malformed Outputs	0.00 (0.00–0.00)	0.91 (0.13–2.08)	0.26 (0.00–0.65)	—
% Infinite Repetitions	4.16 (1.69–7.66)	1.30 (0.13–2.99)	0.00 (0.00–0.00)	—
% Reasoning Leakage	0.00 (0.00–0.00)	1.30 (0.39–2.47)	0.78 (0.00–1.82)	—
% Formatting Leakage	0.00 (0.00–0.00)	14.29 (8.18–21.04)	1.17 (0.13–2.47)	—

Note. WSR = Wilcoxon signed-rank test, computed between Qwen3 thinking mode and TIME across 77 scenario-level comparisons.

Appendix F.1.4: Structural and Behavioral Metrics (32B Models)

Statistic	Qwen3 32B		TIME-32B	WSR <i>p</i>
	No Think	Think		
Benchmark Score	31.82 (25.71–38.31)	37.40 (31.56–43.51)	64.81 (58.18–71.17)	5.0e-07
Chronological Retrospection	61.82 (38.18–83.64)	60.00 (41.82–77.27)	63.64 (45.45–80.00)	—
Invalid Time Detection	11.82 (2.73–25.45)	31.82 (13.64–51.82)	52.73 (32.73–71.82)	—
Temporal Adaptivity	20.00 (1.82–44.55)	26.36 (7.27–47.27)	76.36 (64.55–87.27)	—
Temporal Contextual Awareness	40.00 (13.64–67.27)	43.64 (20.00–69.09)	76.36 (58.18–92.73)	—
Temporal Flow Anomaly Detection	0.91 (0.00–2.73)	3.64 (0.00–8.18)	44.55 (23.64–65.45)	—
Time Gap Awareness	0.91 (0.00–2.73)	3.64 (0.00–7.27)	58.18 (40.00–75.45)	—
Timezone Sensitivity	87.27 (78.18–94.55)	92.73 (83.64–99.09)	81.82 (68.18–92.73)	—
Mean Output Tokens / Run	608.96 (533.37–686.50)	1573.47 (1327.94–1856.57)	332.64 (296.15–371.77)	<1e-08
Mean Thinking Tokens / Run	0.00 (0.00–0.00)	910.52 (705.34–1158.80)	84.16 (71.18–98.27)	<1e-08
Mean # Think Blocks / Run	0.00 (0.00–0.00)	0.99 (0.98–1.00)	1.67 (1.34–2.06)	1.4e-04
% Runs w/ Think Blocks	0.00 (0.00–0.00)	99.22 (97.92–100.00)	80.65 (73.51–87.40)	—
% Heavy Markdown	83.64 (77.01–89.61)	90.91 (85.19–95.71)	62.73 (53.51–71.69)	—
% Light Markdown	95.84 (92.60–98.31)	98.31 (95.45–99.87)	85.45 (79.74–90.65)	—
% Any Degeneracy	4.42 (2.60–6.49)	18.18 (11.43–25.32)	3.64 (1.95–5.97)	4.2e-04
% Malformed Outputs	0.00 (0.00–0.00)	0.78 (0.00–2.08)	1.95 (1.04–2.99)	—
% Infinite Repetitions	4.29 (2.47–6.23)	0.91 (0.00–2.47)	1.30 (0.52–2.34)	—
% Reasoning Leakage	0.13 (0.00–0.39)	0.91 (0.13–1.95)	1.17 (0.52–1.95)	—
% Formatting Leakage	0.00 (0.00–0.00)	17.01 (10.39–24.16)	1.17 (0.13–2.86)	—

Note. WSR = Wilcoxon signed-rank test, computed between Qwen3 thinking mode and TIME across 77 scenario-level comparisons.

Appendix F.2: Phase-wise Ablation Details (32B Models)

Statistic	Qwen3 32B		Phase 1	Phase 2	Phase 3	TIME (32B)
	No-Thinking	Thinking				
Benchmark Score	31.82	37.40	42.47	56.88	52.08	64.81
Chronological Retrospection	61.82	60.00	63.64	52.73	65.45	63.64
Invalid Time Detection	11.82	31.82	39.09	21.82	30.91	52.73
Temporal Adaptivity	20.00	26.36	40.91	80.00	68.18	76.36
Temporal Contextual Awareness	40.00	43.64	48.18	50.00	49.09	76.36
Temporal Flow Anomaly Detection	0.91	3.64	7.27	49.09	40.00	44.55
Time Gap Awareness	0.91	3.64	3.64	59.09	44.55	58.18
Timezone Sensitivity	87.27	92.73	94.55	85.45	66.36	81.82
Mean Output Tokens / Run	608.96	1573.47	1434.56	362.45	294.51	332.64
Mean Thinking Tokens / Run	0.00	910.52	803.52	76.59	52.94	84.16
Mean # Think Blocks / Run	0.00	0.99	0.99	1.12	1.25	1.67
% Runs w/ Think Blocks	0.00	99.22	99.48	95.58	89.22	80.65
% Heavy Markdown	83.64	90.91	88.57	65.32	61.43	62.73
% Light Markdown	95.84	98.31	97.92	83.38	79.48	85.45
% Any Degeneracy	4.42	18.18	13.90	4.68	0.78	3.64
% Malformed Outputs	0.00	0.78	0.52	1.82	0.26	1.95
% Infinite Repetitions	4.29	0.91	0.52	0.39	0.13	1.30
% Reasoning Leakage	0.13	0.91	1.04	2.47	0.26	1.17
% Formatting Leakage	0.00	17.01	12.47	1.17	0.26	1.17