# CMT-Bench: (C)ricket (M)ulti-(T)able Generation (Bench)mark for Probing Robustness in Large Language Models

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#### **Abstract**

LLM Driven text-to-table (T2T) systems often rely on extensive prompt-engineering or iterative event extraction in code-parsable formats, which boosts scores but are computationally expensive and obscure how models actually reason over temporal evolving narratives to summarise key information. We present CMT-Bench, a diagnostic benchmark built from live cricket commentary that requires dynamic table generation across two evolving schemas under a dense, rule-governed policy. CMT-Bench is designed to probe robustness via three semantics-preserving dimensions: (i) extractive-cue ablation to separate extractive shortcuts from state tracking, (ii) temporal prefixing to test long-context stability, and (iii) entity-form perturbations (anonymization, outof-distribution substitutions, role-entangling paraphrases) to assess sensitivity to surface variation. Across diverse long-context stateof-the-art LLMs, we find large drops without extractive summaries, monotonic degradation with input length, and consistent accuracy drop under entity-form changes. Complementary distributional tests confirm significant shifts in numeric error patterns, indicating drift in reasoning rather than mere noise. Our results show that current LLMs are brittle in dynamic Textto-table generation, motivating robustness-first evaluation as a prerequisite for developing efficient and scalable approaches for this task.

#### 1 Introduction

Tables are a universal medium for structuring information, underpinning applications in scientific reporting, finance, sports analytics, and business intelligence by enabling compact storage, comparison, and retrieval of facts. Inferring structured summaries from dense, unstructured text, also known as Text-to-Table Generation (T2T), has gained importance. Early work framed T2T as an information extraction task (Wu et al., 2022; Li et al., 2023; Sundar et al., 2024; Pietruszka et al., 2024) em-

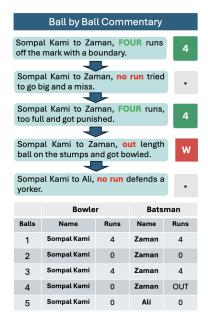


Figure 1: Ball by Ball Commentary in Cricket and updation of Batsman and bowler Tables with every ball

phasizing structural integrity and cell alignment where as recent works (Tang et al., 2024; Hu et al., 2024; Ahuja et al., 2025) explore more challenging paradigms going beyond simple extraction, incorporating temporal reasoning over long-contexts for generating summarized representations (Deng et al., 2024a; Ahuja et al., 2025). However, most of these approaches 1. are prompt-based and are only effective on frontier LLMs (Gpt-4o, Gemini-2.5, etc.) 2. rely on iterative extraction of events in a code-parsable format, leading to increased computational costs 3. are tested on only one dynamic generation benchmark (Livesum) due to a scarcity of high-quality datasets that test summarization over temporally evolving data.

Moreover, it is hard to discern whether models truly *reason* or simply exploit brittle surface cues and distributional regularities. Additionally, all of these studies show negative to no improvements using standard boosting techniques, such as

Dataset	Task	Multi-table	Dynamic Schema	Avg. Tokens
RotoWire	Extraction	<b>√</b>	✓	347
WikiBio	Extraction	X	X	95
WikiTableText	Extraction	X	X	14
E2E	Extraction	X	X	27
Livesum	Counting	X	X	1,571
SportsMetrics	Count. + Reas.	X	✓	6,229 / 6,166
CMT-Bench	Count. + Reas. + Extr.	✓	✓	9435

Table 1: Comparison of text-to-table benchmarks. Extraction refers to tasks where values from input text are directly placed in tables. Counting refers to tasks that require counting the number of events that uniformly increment by 1, eg, Wickets, Balls. Reasoning refers to tasks that require contextual understanding, for eg, A Maiden Over refers to consecutive six deliveries by a bowler giving 0 runs.

in-context learning (Brown et al., 2020) and finetuning approaches (Hu et al., 2022). These gaps motivate a diagnostic study on Text-to-Table, understanding how models actually reason as a prerequisite to designing efficient, scalable systems for this task.

We introduce **CMT-Bench**, a diagnostic benchmark built from live cricket commentary that requires *dynamic text-to-table generation* across two evolving tables (batsmen and bowlers) governed by a complex policy (game rules). CMT-Bench focuses on long-context state tracking, entity resolution, and cross-span aggregation, enabling controlled robustness probes along three broad dimensions that expose model brittleness. By centering evaluation on these invariances, our study comprehensively examines whether models maintain identity-consistent numeric states and preserve correctness beyond clean, cue-rich inputs. We make the following contributions:

- We release CMT-BENCH, a long-context T2T benchmark consisting of over 6500 cricket commentary samples and ground-truth tables along with a label-invariant perturbation suite.
- We benchmark diverse long-context State-ofthe-art LLMs isolating (i) reliance on extractive summaries and (ii) temporal robustness.
- We propose a principled study to audit robustness for Table generation tasks across three key dimensions, coupling performance with distributional testing (blocked permutation + energy distance) to quantify shifts in numeric error patterns.

## 2 CMT-Bench

Cricket commentary presents substantially greater challenges for structured generation than other sports domains, such as football (Deng et al., 2024a) or basketball (Wiseman et al., 2017; Hu et al., 2024). Each innings involves multiple interacting entity types(batsmen, bowlers, and fielders), each governed by distinct and interdependent attributes that evolve continuously over time. A single innings may span up to 300 ball-by-ball events ( $\approx 3.5$  hours), demanding long-context reasoning and sustained state tracking. Unlike other sports where events can be locally resolved, cricket statistics depend on multi-level reasoning: counting (balls faced, runs conceded), categorical aggregation (boundaries, extras), and localized inference (a "maiden over" requiring verification across the last six deliveries). This combination of dense temporal structure, multi-entity interaction, and contextdependent computation makes cricket a uniquely rigorous testbed for evaluating the robustness of LLMs in dynamic text-to-table generation. A comparison of CMT-Bench with other T2T datasets is presented in Table 1.

#### 2.1 Dataset Collection and Preprocessing

We collect ball-by-ball commentary data from **Cricinfo**<sup>1</sup>, which provides detailed textual descriptions of cricket matches. To ensure chronological integrity and remove non-play content (e.g., weather updates, advertisements), we apply a monotonicity filter based on two criteria: (i) **Entity presence:** both the bowler and batsman names must co-occur in the line, separated by the standard delimiter pattern used across commentaries; and (ii) **Action presence:** the line must include a valid gameplay outcome such as *no run*, *FOUR*, *OUT*, or an extra (e.g., *Iw*, *Inb*). This filtering retains only gameplay-relevant utterances, discarding weather updates, banter, and pre- and post-match interviews. Our base dataset comprises **498 ODI** 

https://www.espncricinfo.com/

innings  $(2006-2025)^2$  and 116 T20 innings from the 2025 Indian Premier League (IPL)<sup>3</sup>. To analyze model performance across varying context lengths, we additionally create truncated samples by slicing the first x (120/180/240) balls of randomly selected samples, enabling systematic evaluation of temporal robustness and the effect of input length on model consistency. After incorporating these sliced variants, the dataset expands to a total of 1,362 ODI samples and 270 T20 samples. All data are sourced from publicly available pages under fair-use terms for academic research. A sample commentary and corresponding ground-truth tables are provided in Appendix A.1.

#### 2.2 Ground Truth Creation

For each commentary sample, we construct two structured tables summarizing player performance: one for batsmen and one for bowlers.

- **Batsman Tables** include *runs*, *balls faced*, *fours*, *sixes*, and *strike rate* (*S/R*). These attributes require both counting (e.g., runs and boundaries) and arithmetic reasoning (e.g., strike rate = runs/balls). Models must also handle figurative boundary expressions and implicit event cues within commentary text.
- **Bowler Tables** include *balls*, *runs conceded*, *wickets*, *overs*, and *maidens*. Bowling statistics require cross-span reasoning, e.g., identifying a maiden over demands tracking six consecutive deliveries with zero runs, and careful attribution of extras (wides, no-balls, byes)

Each innings is segmented into ball-level events using regular expressions (regex) (pseudocode provided in Appendix A) based on Cricinfo's standard notation (e.g., 3.2: Starc to Kohli corresponds to over 3, ball 2, bowler = Starc, batsman = Kohli). A domain-specific regex parser then extracts event outcomes such as runs scored, boundaries, and wickets. Cricket extras (wides, no-balls, byes, legbyes) are parsed deterministically due to their asymmetric impact on batsman and bowler statistics. Wides and no-balls add to the bowler's runs conceded but not to the batsman's tally; however, no-balls count as balls faced if the batsman scores from them. Byes and leg-byes contribute to the

team total but are excluded from both player tables. This rule-based alignment ensures numeric and statistical consistency across all entities. Each ball-level event is decomposed into its constituent entities (as detailed in Point 5 of A), after which the batsman and bowler scorecards are derived by grouping these structured entries by player name. This aggregation ensures that all per-ball statistics are correctly accumulated under their corresponding batsman or bowler, forming the ground-truth tables used for evaluation. An example showing a brief 5-over commentary and its respective batsman and bowler scorecard has been shown in A.1 and tables 6,7.

#### 2.3 Ground-Truth Validation

Since all ground-truths are generated programmatically, it becomes imperative to validate the correctness of the benchmark. This is done using two studies. For all samples containing full match commentary, we compare the generated ground-truths with publicly available summary scorecards and find 99.7% exact match. Further, for samples generated by slicing, the authors manually validate 500 samples each and find 99.3% exact match for each statistic (cell value) and 100% accuracy for entities (row headers), hence confirming the correctness of CMT-Bench.

#### 3 Robustness Study Design

Despite rapid progress in long-context LLMs, mounting evidence shows that models often exploit brittle surface cues, memorize entity strings, or overfit to annotation artifacts rather than performing stable, semantics-preserving reasoning. For table generation tasks, we define robustness as invariance of the produced tables under perturbations that do not change the underlying events: removing extractive summaries, varying the input length, or altering entity surface forms (aliases, delexicalization, paraphrase). Cricket commentary is well-suited for probing these behaviors because (i) gold scorecard tables are deterministic functions of events, (ii) entity roles (bowler → batsman) must be maintained across long horizons, and (iii) surface variation is common yet label-invariant.

We adopt a threat model that tests robustness of LLMs across three dimensions while preserving the gold labels: (a) extractive shortcuts, where models key on dismissal lines or embedded summaries; (b) long-context fragility, where early er-

<sup>&</sup>lt;sup>2</sup>One Day International of approximately 300 balls, played between national teams.

<sup>&</sup>lt;sup>3</sup>Twenty-over games consisting of approximately 120 balls.

rors propagate as horizons grow; and **(c) entity- form sensitivity**, where performance depends on lexical familiarity or canonical formatting rather than role reasoning. In all cases, the *events* and *scorecard schema* remain unchanged. Guided by this threat model, we study the following research questions:

**RQ1.** Extractive cues vs. reasoning: How robust are models when summary cues are removed from commentary?

**RQ2. Temporal robustness:** How does performance scale with increasing context size, with and without summary cues?

**RQ3.** Entity-form robustness: How robust are models to semantics-preserving changes in entity surface forms (e.g., anonymization, OOD substitutions, role-entangling paraphrases), and do these changes induce systematic shifts in the output error distribution? For each of these dimensions, we now present the experimental design:

#### 3.1 RQ1: Extractive cues vs. reasoning

Cricket commentaries often contain summary cues that can greatly aid in tabular summarization. These are summarised statistics given for batsmen, usually when they get out. For e.g. *Mosaddek Hossain run out (Chakabva) 5 (9b 0x4 0x6 21m) SR: 55.55*. These can help the model extract aggregated values directly without having to maintain states over dynamic inputs, essentially reducing reasoning to simple extraction. We test to what extent models rely on these embedded summary cues by removing such texts (WITH-SUMMARY and WITHOUT-SUMMARY) from the inputs using deterministic rules that can identify such cues easily built to parse Cricinfo's standard commentary notation as discussed in 2.2

## **3.2** RQ2: Temporal robustness (with/without summary cues)

These experiments aim to analyze how performance varies as the input horizon grows and whether this temporal effect depends on the presence of summary cues. For each innings, we construct partial inputs by progressively extending the commentary in 5-over (30 balls) increments up to the full innings (ODI:  $5\rightarrow 50$ ), and for every prefix we evaluate both WITH-SUMMARY and WITHOUT-SUMMARY. Gold tables are recomputed up to the prefix so that labels remain invariant under truncation.

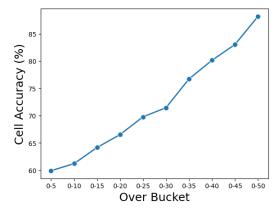
#### 3.3 RQ3: Entity-form robustness

To comprehensively understand whether models genuinely *reason* over input rather than keying on brittle surface cues, we probe *form robustness*: sensitivity to changes in phrasing, entity surface forms, and language. Concretely, we introduce 3 perturbation types and evaluate the difference in accuracy using the temporal samples as a baseline. Moreover, we perform a thorough statistical analysis to diagnose shifts in the output distribution of each model under a given perturbation, which is discussed in . The perturbations introduced are as follows:

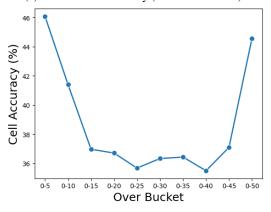
- Anonymization: Names of all player mentions are replaced with symbolic placeholder (e.g., player1, player2). This process mirrors the *delexicalization* strategy used in (Suntwal et al., 2019), to encourage the model to focus on relational and factual reasoning rather than lexical memorization.
- Entity Substitution: Player names are replaced with *synthetic but plausible, human-sounding names* drawn from entirely different domains: for example, "Arun Hiachak to Lionel Cristiano" instead of "Muzarabani to Tamim."<sup>4</sup>
- Entity-Entanglement: Entity Entanglement: Commentary lines are paraphrased to break the standard "<bowler> to <bases> structure, embedding player names within descriptive phrasing: for example, "Between Tamim and Muzarabani: no run past the outside edge to the batter. Fullish length in the off-stump channel, as Tamim presents his bat playing in the line and the ball shoots off the pitch" instead of "Muzarabani to Tamim, no run." In this form, the roles of bowler and batsman are no longer explicitly stated, and while contextual cues (e.g., delivery descriptions, batting actions) may still allow inference, such cues are not guaranteed for every delivery. Consequently, LLMs must holistically interpret the entire commentary segment and reason across multiple lines and contextual signals to correctly infer player roles and maintain scorecard consistency.

An example for each perturbation is provided in Appendix C.

<sup>&</sup>lt;sup>4</sup>Lionel Cristiano: **Lionel** Messi + **Cristiano** Ronaldo, two very famous soccer players.



(a) Batsman cell accuracy (Gemini 2.5 Flash).



(b) Bowler cell accuracy (Gemini 2.5 Flash).

Figure 2: Temporal cell accuracy trends with summary cues for (a) batsman and (b) bowler tables.

#### 3.4 Models

We evaluate six state-of-the-art LLMs (Gemini-2.5-Flash, Llama-3.3-70B-Instruct-Turbo, Llama-3.1-8B-Instruct(Grattafiori et al., 2024), Qwen-2.5-72B-Instruct, Owen-2.5-7b-Instruct(Owen et al., 2025), **GPT-40 mini**(OpenAI et al., 2024)). Since the commentaries of cricket are an average of 9k tokens, we choose models with context length over 32k tokens. Consistent model temperature (0.1) and top-p (0.1) are maintained for deterministic outputs. Prior studies (Deng et al., 2024b)(Ball et al., 2024) have demonstrated that Zero-Shot Chain-of-Thought (ZS-CoT) prompting achieves superior performance on table generation tasks when compared to few-shot prompting; therefore, we adopt this prompting strategy to evaluate all models in our experiments. Prompt used is provided in Appendix B.

#### 3.5 Evaluation Metrics

State-of-the-art Table evaluation metrics (Pancholi et al., 2025; Ramu et al., 2024; Jain et al., 2024)

	With / Without Summary Cues										
Models	В	atsma	n	Bowler							
	Cell	Col	Row	Cell	Col	Row					
Gemini	89 / 49	20 / 0	80 / 17	55 / 45	20 / 20	18/9					
2.5 Flash	-40	-20	-63	-10	0	-9					
Llama	87 / 39	0/0	78 / 8	41 / 37	20 / 20	4/2					
( <b>70b</b> )	-48	0	-70	-4	0	-2					
Qwen	85 / 34	0/0	75 / 6	37 / 38	20 / 40	1/1					
( <b>72b</b> )	-51	0	-69	+1	+20	0					
Llama	87 / 39	20 / 4	78 / 8	41 / 37	17/9	3/3					
(8b)	-48	-16	-70	-4	-8	0					
Qwen	72 / 24	2/0	48 / 2	21 / 21	3/3	0/0					
( <b>7b</b> )	-48	-2	-46	0	0	0					
GPT	84 / 29	0/0	74 / 3	35 / 32	0/0	1/1					
40 mini	-55	0	-71	-3	0	0					

Table 2: Cell Accuracy (Cell), Column Accuracy (Col), Row Accuracy (Row) for batsman and bowler tables across models for cricket commentaries **With and With-out Summary** 

primarily utilize LLM-driven frameworks that can capture structural fidelity and information loss beyond factual correctness. In our setting, however, the output tables are purely statistical batsman and bowler scorecards with a fixed schema and canonical units (counts for runs/balls/wickets), reducing correctness to numeric agreement under known constraints. We first align predicted and gold entities by normalizing names (lowercasing, whitespace removal) and computing a composite similarity (60% token-overlap + 40% SequenceMatcher). We resolve the similarity matrix with the Hungarian algorithm and keep only alignments above 0.35 to prevent spurious matches while tolerating minor noise. Post-alignment, we report Cell Accuracy (exact numeric agreement over all cells across both tables), Row Accuracy (entity-level correctness), and Column Accuracy (attribute-level correctness).

#### 4 Results

#### 4.1 RQ1: Exraction Cues v/s Reasoning

From Table 2, we observe that even with helpful cues, state-of-the-art frontier models like Gemini-2.5-flash achieve 89% accuracy on the cell level and 49% at the row level, going as low as 72% for cell and 2% for row for Qwen-7B. Column-level accuracies are consistently low for all models (20% for Gemini, 3% for Qwen-7B). Model performance drops significantly (-42% avg. on cell level and -87% avg. on row level) when summary cues are

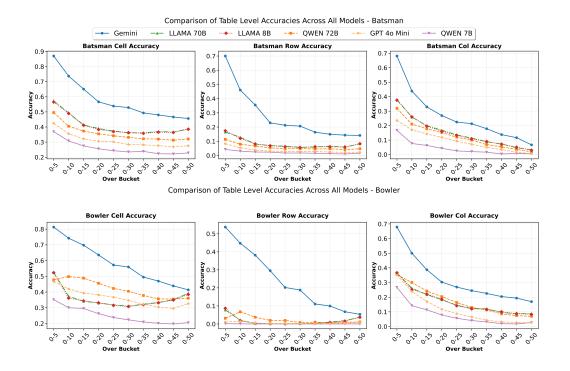


Figure 3: Temporal Trend of Accuracy on Cricket Score Tables

	AUC for Scorecards					
Models	Batsman	Bowler				
Gemini 2.5 Flash	3.25	3.35				
Llama (70b)	1.87	1.57				
<b>Qwen (72b)</b>	1.59	1.83				
Llama (8b)	1.85	1.56				
Qwen (7b)	0.94	0.95				
GPT 4o mini	1.28	1.41				

Table 3: Area under curve (AUC) computed by averaging row, column, and cell accuracies across overs for commentary without summary cues. Higher values indicate stronger temporal consistency.

removed. Row-level accuracies are hit hardest, justifiably, as these summary cues directly contain all the relevant attributes for an entity. Contrastively, column-level accuracies show the lowest drop (-9%), possibly as they are generally harder to track as summary cues for a column are spread throughout the context, which don't offer much help in the first place. The results indicate that LLMs behave as high-precision extractors, but once cues are withheld, they struggle to infer the same information through reasoning over numerical dependencies. The limited degradation observed for bowlers further underscores that reasoning over cumulative continuity (overs, maidens) is less reliant on

surface-level textual scaffolding than reconstructing batsman progressions. We also compute individual accuracy across all columns discussed in Appendix D.

#### 4.2 RQ2: Temporal Robustness

We first examine temporal trends in cell accuracy using commentary with summary cues whose results has been shown in Figure 2. Surprisingly, batsman cell accuracy rose steadily across overs, while bowler accuracy dipped early and recovered toward the end. This counter-intuitive pattern arises from summary cues, explicit mentions of dismissals or milestones that allow direct extraction rather than inference. As wickets fall, such cues become more frequent, inflating batsman accuracy without reflecting genuine reasoning. The late-innings recovery for bowlers, in contrast, suggests that models could be leveraging memorized lexical templates rather than genuine temporal reasoning.

Motivated by these findings, we re-evaluated the temporal trend in cell-, row- and column accuracies without summary cues, requiring models to infer scorecards purely through reasoning. As shown in Figure 3, batsman accuracy now declined monotonically with increasing input length, demonstrating that performance gains under summaries were largely extractive. The decline stabilized between overs 20–30, corresponding to the middle-overs

phase when fewer events occur and contextual drift is reduced.

For bowlers, accuracy curves were flatter in both settings, consistent with the commentary's batsman-centric bias. Even so, their smaller fluctuations and weaker cue dependence suggest that bowling reconstruction depends more on temporal continuity and aggregate reasoning. Notably, the with-summary analysis was conducted for Gemini 2.5 Flash, while without-summary results extend across multiple models.

To quantify the temporal trends observed earlier, we computed the area under the accuracy curve (AUC) by averaging cell-, row-, and column-level accuracies across overs. This provides a single measure of each model's consistency over time.

As shown in Table 3, Gemini 2.5 Flash achieves the highest AUC for both batsman (3.25) and bowler (3.35) tables, followed by LLaMA-3.3-70B, LLaMA-3.1-8B, Qwen 2.5-72B, GPT-4o-mini, and Qwen 2.5-7B. Notably, Qwen 72B surpasses both LLaMA variants on the bowler table, suggesting stronger temporal reasoning and reduced dependence on surface cues.

Overall, the AUC trends confirm that larger and reasoning-oriented models maintain performance more consistently across innings, while smaller models degrade with longer contexts.

#### 4.3 RQ3: Entity Form Robustness

As shown in Table 4, we observe that almost every model exhibits deviation in accuracy when compared with the original text. Notably, both variants of the Qwen models (7B: cell: -17.2%, col: -53%), (72B: cell: -7.6%, col: -33%) show a significant drop in performance across all perturbation types. The Llama family of models (8B: cell: -4.9%, col: -24%, 72B: cell: -3.5%, col: -22.5%), while more stable than qwen, also exhibits a performance drop. Gemini shows surprising improvement/stable performance across all perturbation types, specifically on Anonymization and Entity Substitution perturbations. GPT-40-mini shows the least deviation across all perturbation types.

To further understand whether models get confused between entity roles, swapping batsman and bowler names, we apply Jaccard similarity between the Ground-truth batsman and model-generated bowler tables (and vice-versa). We observe up to 13% for anonymized variant and upto 16% increase for entity-entanglement in similarity scores. Taken together, several broad patterns emerge. All

models degrade substantially without summaries, confirming the importance of dismissal cues. Entity Entanglement is universally damaging, with entity accuracy dropping by 15–20 points. OOD Entity Substitution and Anonymization perturbations split the models: Gemini gains from both, while Qwen and LLaMA models degrade, underscoring divergent strategies for entity resolution. In terms of relative strength, GPT-40-mini and Gemini stand out for their robustness, achieving high accuracy under unmasking and maintaining stability under counterfactuals. LLaMA-70B performs strongly when cues are explicit but proves brittle under paraphrasing and abstraction.

## 5 Statistical Analysis: Does Changing Surface Entity Forms Affect LLM Reasoning?

For text-to-table generation where counting and aggregation are central, robustness should entail not only comparable means but also invariant distributional shape across errors, showing stable reasoning. Complementing our accuracy analysis, we next investigate whether *error distributions themselves remain stable across different entity forms*. This helps quantify the effect of perturbing surface entity forms on underlying reasoning patterns for models.

## 5.1 Distributional Robustness: Hypothesis Testing Framework

Following recent robustness-auditing frameworks (Rauba et al., 2025), we perform Hypothesis testing to quantify and substantiate the drift in error distributions caused by each perturbation on the model outputs. Acknowledging the inherent difference in the ability of each model for Text-totable tasks, we perform blocked permutation tests for each (model, perturbation)pair with the unperturbed outputs, which allows for a quantitative analysis of **a**) Which perturbation causes the most drift in LLMs?, and **b**) Which models are more robust to perturbations?

**Setup:** Let  $\mathcal{I}$  denote the set of samples,  $\mathcal{M}$  the set of Models, and P be the set of perturbations.

Each sample yields two tables (batsman, bowler) with numeric fields:

 $\mathcal{S} = \{ \texttt{Balls\_Faced}, \texttt{Runs}, \texttt{Fours}, \texttt{Sixes}, \texttt{S/R}, \texttt{Balls}, \texttt{Overs}, \texttt{Runs\_Given}, \texttt{Wickets}, \texttt{Maidens} \}, K = |\mathcal{S}|.$ 

For sample i, model m, perturbation p, and column  $s \in \mathcal{S}$ , let  $e_{i,m,p}(s)$  be the scalar error vector

P	Anonym	ization (	Original	/ Anony	mized)	
Models	]	Batsman	1		Bowler	
	Cell	Column	Row	Cell	Column	Row
Gemini	52 / 56	20 / 40	19 / 28	52 / 57	20 / 60	16 / 22
2.5 Flash	+4	+20	+9	+5	+40	+6
Llama	38 / 35	0/0	7/6	34 / 31	20/0	1/0
(70b)	-3	0	-1	-3	-20	-1
Qwen	33 / 31	0/0	5/4	40 / 38	20 / 20	2/1
(72b)	-2	0	-1	-2	0	-1
Llama	38 / 36	10/9	7/6	34 / 31	13 / 10	1/0
( <b>8b</b> )	-2	-1	-1	-3	-3	-1
Qwen	24 / 16	2/0	2/0	23 / 20	4/3	0/0
( <b>7b</b> )	-8	-2	-2	-3	-1	0
GPT	29 / 28	0/0	3/2	34 / 32	0/0	0/0
40 mini	-1	0	-1	-2	0	0
					nal / Entit	ty subs)
		Column			Column	Row
Gemini	52 / 59	20/0	20 / 32	52 / 62	20 / 40	16 / 28
2.5 Flash	+7	-20	+12	+10	+20	+12
Llama	38 / 37	0/0	7/7	34 / 33	20 / 20	1/1
( <b>70b</b> )	-1	0	0	-1	0	0
Qwen	34 / 34	66 / 66	5/5	40 / 38	20/0	2/1
(72b)	0	0	0	-2	-20	-1
Llama	38 / 37	10 / 10	7/7	34 / 32	13 / 12	1/1
(8b)	-1	0	0	-2	-1	0
Qwen	24 / 19	2/2	2/1	23 / 21	4/5	0/0
(7b)	-5	0	-1	-2	+1	0
GPT	29 / 29	0/0	3/3	34 / 34	0/0	1/1
40 mini	0	0	0	0	0	0
					l / Entan	
		Column			Column	Row
Gemini	51 / 52	20/0	20 / 23		20 / 40	16 / 17
2.5 Flash	+1	-20	+3	+1	+20	+1
Llama	38 / 33	0/0	7/4	34 / 36	20/0	1/2
(70b)	-5	0	-3	+2	-20	+1
Qwen	34 / 29	0/0	5/3	40 / 34	20/0	2/0
(72b)	-5	0	-2	-6	-20	-2
Llama	38 / 33	10/5	7/4	34 / 36	12 / 11	1/2
(8b)	-5	-5	-3	+2	-1	+1
Qwen	24 / 19	2/0	2/0	22 / 21	4/1	0/0
(7b)	-5	-2	-2	-1	-3	0
GPT	29 / 26	0/0	3/2	34 / 31	0/0	1/0
40 mini	-3	0	-1	-3	0	-1

Table 4: Comparison of Cell, Row and Column Accuracy with Original Samples for each Entity-form Perturbations for all Models

defined as:

$$e_{i,m,p}(s) = \frac{1}{|\mathcal{M}_{i,m,p}(s)|} \sum_{\hat{r} \in \mathcal{M}_{i,m,p}(s)} \left| \widehat{T}_{i,m,p}(\hat{r},s) - T_i(\pi_{i,m,p}(\hat{r}),s) \right|. \quad (1)$$

Where  $T_i(r,s)$  is the ground-truth value,  $\widehat{T}_{i,m,p}(\hat{r},s)$  is the model prediction,  $\pi_{i,m,p}$  is the one-to-one alignment from predicted rows to ground-truth rows (from 3.5) and  $\mathcal{M}_{i,m,p}(s)$  is the

set of matched predicted rows used for column s. Each (i, m, p) yields a K-dimensional error vector  $\mathbf{e}_{i,m,p} = (e_{i,m,p}(s_1), \ldots, e_{i,m,p}(s_K))$ . To ensure comparability across columns, we standardize within model:

$$z_{i,m,p}(s) = \frac{e_{i,m,p}(s) - \mu_m(s)}{\sigma_m(s)}, \ \mathbf{z}_{i,m,p} = (z_{i,m,p}(s))_{s \in \mathcal{S}}.$$

Means  $\mu_m(s)$  and std.  $\sigma_m(s)$  are computed using the union of clean and target perturbation samples.

**Hypothesis test.** For model m and perturbation p, let

$$X_m = \{\mathbf{z}_{i,m,\text{original}}\}, \quad Y_{m,p} = \{\mathbf{z}_{i,m,p}\},$$

We test whether the multivariate distributions differ:

$$H_0: \mathcal{L}(X_m) = \mathcal{L}(Y_{m,p})$$
 vs.  $H_1: \mathcal{L}(X_m) \neq \mathcal{L}(Y_{m,p})$ .

**Energy distance.** Using the Euclidean norm  $\|\cdot\|$ , the energy distance is

$$\mathcal{E}(X, Y) = 2 \,\mathbb{E}||X - Y|| - \mathbb{E}||X - X'|| - \mathbb{E}||Y - Y'||,$$

estimated via unbiased pairwise distances. Larger  ${\cal E}$  indicates stronger distributional shift in both mean and dispersion.

**Blocked permutation test:** Under  $H_0$ , clean and perturbed labels are exchangeable within each paired item. We generate B random permutations by flipping each pair  $(\mathbf{z}_{i,m,\text{clean}},\mathbf{z}_{i,m,p})$  with prob. 1/2, recomputing  $\mathcal{E}^{(b)}$  each time. The two-sided p-value is

$$p_{\text{perm}} = \frac{1 + \sum_{b=1}^{B} \mathbb{I}\{\mathcal{E}^{(b)} \ge \mathcal{E}_{\text{obs}}\}}{1 + B}.$$

This design controls for column-wise difficulty (pair-level blocking) and model ability, hence allowing us to compare model robustness and perturbation effect across models.

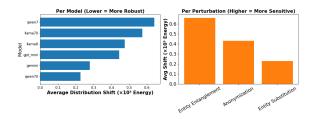


Figure 4: Comparison of avg. distribution shifts across models (left) and perturbation types (right). Lower shift values indicate higher robustness.

		Perturbation	on
Model	Anon.	<b>Entity Sub.</b>	Entangle.
Gemini-2.5	0.132	0.316	0.387
Llama-70B	0.313	0.277	1.133
Qwen-72B	0.169	0.023	0.488
Llama-8B	0.335	0.160	0.929
Qwen-7B	1.083	0.538	0.305
GPT-40 mini	0.558	0.062	0.713

Table 5: Observed effect ( $\mathcal{E}_{obs}$ ) of each perturbation with 99.995% confidence, p < 0.005

#### 5.2 Findings

We run the Blocked permutation test for B=2000 epochs and report the observed effect  $\mathcal{E}_{obs}$  for each perturbation on each model in Table 5. For every experiment, we achieve a significant effect (p < 0.005) of each perturbation, validating that all models significantly drift in errors when perturbed. Moreover, as shown in Figure 4, we see clear trends in the effect of perturbations on models. Entityentanglement shows the highest drift in distribution, also validated by the biggest performance drops discussed in 4.3. Anonymization shows the next highest shift, followed by entity substitution. At the model level, we find that Qwen-70 and Gemini-2.5 are the most robust among all, although they also drift significantly. These findings strongly point to existing issues with state-of-the-art LLMs simply memorizing entity names, showing significant accuracy drops and distributional shifts across different perturbations. Further analysis about effect of particular columns on distribution shift is provided in Appendix D.1.

#### 6 Related Work

Auditing the robustness of language models has become a critical area of research, moving beyond simple accuracy metrics to more rigorously probe model behaviors. A large body of work demonstrates that high average performance can often mask underlying fragilities and reliance on spurious correlations. Methodologies have evolved to include behavioral testing with checklists to evaluate specific linguistic capabilities (Ribeiro et al., 2020), adversarial and counterfactual examples to assess sensitivity to minor input perturbations (Jia and Liang, 2017; McCoy et al., 2019; Kaushik et al., 2020), and analyses of long-context reasoning to identify performance degradation over extended inputs (Liu et al., 2024). These diagnostic approaches are essential for understanding model limitations and are increasingly important for informationcentric tasks, where reliability and faithfulness to source material are paramount.

The task of text-to-table (T2T) generation has similarly matured from a structured information extraction (IE) problem to a more complex reasoning challenge. Recent approaches have tackled increasingly complex settings where table values must be derived through aggregation, counting, and tracking state changes over long, narrativestyle texts. Systems now address nuanced domains like sports analytics (Hu et al., 2024) and finance (Zhu et al., 2024), generate complex hierarchical tables (Cheng et al., 2021) and employ sophisticated schema-guided pipelines or iterative event extraction (Ahuja et al., 2025; Deng et al., 2024a). As T2T systems take on these more demanding reasoning tasks, the need for robust evaluation, drawing on the principles of model auditing, becomes indispensable for ensuring their reliability.

#### 7 Conclusion

We present CMT-BENCH, a diagnostic benchmark for dynamic text-to-table generation from live cricket commentary, and use it to study robustness across diverse long-context LLMs. Three key findings emerge: models rely heavily on extractive dismissal summaries (large row-level drops once removed), performance degrades with longer horizons without cues (error accumulation and difficulty with identity-consistent aggregation), and semantics-preserving changes to entity forms sharply reduce accuracy, especially under roleentangling paraphrases accompanied by significant shifts in numeric error distributions confirmed via blocked-permutation tests. Together, these results indicate reasoning drift under small input changes and highlight a gap between extraction and genuine state tracking in T2T. We hope CMT-BENCH catalyzes robustness-first methods that are both efficient and reliable for long, noisy, and open-domain Text-to-table generation.

#### Limitations

Our study is intentionally diagnostic and scoped to dynamic text-to-table generation from live cricket commentary. While this domain offers dense, rulegoverned structure and label-invariant perturbations, it is a single setting with its own stylistic conventions and entity distributions. Model coverage is representative rather than exhaustive, reflecting current long-context availability. A further limitation is that our evaluation emphasizes numeric fidelity under a fixed schema and does not include tables with a greater variety of features, such as dates, time, merged cells, and hierarchical tables required by domains such as finance, healthcare. Finally, our perturbation suite targets semantics-preserving edits (cue ablation, temporal scaling, entity-form changes) and does not audit other sources of variation, such as broadcaster style, multilingual code-switching beyond our examples, or potential sensitivity to demographic patterns in names.

These choices suggest several concrete extensions. First, broadening domain coverage to nonsports narratives with dynamic aggregation (financial filings, clinical trial reports, scientific summaries) could validate out-of-domain generalization and multilingual robustness. Second, enriching the perturbation family with source/style variation, code-mixing, and fairness-oriented probes, pairing accuracy with human-in-the-loop error attribution to separate structural inconsistencies from reasoning drift. Third, translating findings into methods via lightweight test-time scaling (constrained/consistency decoding with alignment-aware voting) or rule-/schema-aware state updates that enforce conservation constraints (balls $\rightarrow$ overs, runs $\rightarrow$ S/R, maidens) could significantly advance research efforts in advancing LLMs table generation capabilities.

#### Acknowledgement

We thank the members of the CoRAL<sup>5</sup>, ASU for their valuable feedback and thoughtful suggestions throughout this project, which materially improved the clarity and rigor of our work. We also thank the Sol Computer cluster at Arizona State University for providing the compute resources that made our experiments possible.

#### **Ethics Statement**

All data used in this study was collected exclusively from publicly accessible webpages on ESPN-cricinfo <sup>6</sup>, a widely used platform that provides live commentary and statistics on cricket matches. The dataset consists of ball-by-ball textual descriptions and associated player names, which are already publicly available in broadcast and written formats.

No private, sensitive, or personally identifiable information beyond publicly known professional athlete names was collected. The scraping process followed a minimal and non-intrusive approach, ensuring that only relevant gameplay commentary was retained while discarding extraneous content such as advertisements, banter, or non-match updates

The resulting dataset was used strictly for academic research purposes, with the goal of creating a benchmark to evaluate language model robustness in text-to-table generation. We recognize that the use of real player names introduces potential concerns regarding memorization or unintended associations. To mitigate this, we explicitly designed robustness experiments that include anonymization and entity substitution, ensuring that the benchmark can be studied without reliance on individual identities. This research does not attempt to commercially exploit the data, nor does it aim to generate derivative works that could misrepresent or harm the reputations of individual players, teams, or organizations. All outputs remain within the scope of scholarly inquiry and reproducible evaluation. The dataset and benchmark are shared under fair-use provisions for research, with appropriate attribution to the original source platform. We have used AI tools such as ChatGPT for assistance in writing, find relevant literature and assistance in coding.

#### **Licence Statement**

The benchmark artifacts (ground-truth tables, perturbations, and evaluation code) are released under the Creative Commons Attribution—NonCommercial—ShareAlike 4.0 International (CC BY-NC-SA 4.0) license. This permits use, distribution, and adaptation for academic research purposes only, provided that appropriate credit is given and derivative works are shared under the same terms.

The dataset includes structured representations derived from commentary text publicly available on ESPNcricinfo. Original commentary remains under ESPNcricinfo copyright and is redistributed here solely under fair-use provisions for non-commercial research. Commercial use of these artifacts is strictly prohibited.

<sup>&</sup>lt;sup>5</sup>https://coral-lab-asu.github.io/

<sup>6</sup>https://www.espncricinfo.com/

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### A Appendix A: Ground Truth Generation

#### **A.1** Structuring Commentary from CricInfo

We convert every ball bowled into a structure using regexes to extract the batsman and bowler entities which always have a pattern. We also extract the runs that comes off that bowl to keep tracking the numerical attributed linked to bowler and batsman. The pseudocode for the same has been explained below.

Input: raw\_commentary\_text

```
1) Segment into balls
   - Find over markers with regex: r"\b
    ([0-4]?[0-9]\.[1-6])\b"
   - For each adjacent pair of matches, slice
    text between them 
ightarrow ball_chunk
2) Parse each ball_chunk
   - Split by lines 
ightarrow L
   - over := float(first space-token in
    ball_chunk) // from L joined/split by
    spaces
   - run_token := normalize(L[1]); map "•"→"0"
   - Extract bowler, batter from L[2] using:
       regex: r"^(?P<bowler>.+?) to (?P<batter
    >.+?)," \rightarrow groups["bowler"], groups["batter"
   - commentary := concatenate L[2:] until any
    stop condition:
       * contains "CRR:" or "end of over"
       * contains time token via regex: r"\b\d
    {2}(?:am|pm)\b" (case-insensitive)
       * contains " SR: "
     (Stop at first hit; keep preceding text.)
3) Derive per-ball features
   - Team runs increment:
       if run_token starts with digit \rightarrow int(
    run_token[0]); else 0
   - Batter runs:
       if regex r"^d+" \rightarrow int(run_token)
       elif regex r"^d+nb" \rightarrow int(first digit)
       else 0
   - Batter 4/6:
       four := 1 if (run_token == "4" or regex r
    "^4(?!lb)") else 0
       six := 1 if (run_token == "6" or regex r
    "^6(?!lb)") else 0
   - Batter ball faced:
       1 if (regex r"^\d+$" or run_token == "W"
    or (no 'w' in run_token)) else 0
   - Bowler legal ball:
```

```
1 if (regex r"^\d+$" or (no 'w' and no '
nb' in run_token)) else 0
- Bowler runs conceded:
   if regex r"^\d+$" \rightarrow int(run_token)
    elif regex r"^\d+(?:w|nb)$" \rightarrow int(first digit)
    else 0
- Wicket (bowler credit):
   if run_token == "W" AND commentary contains any dismissal keyword:
        [" st "," c "," lbw "," hit wicket "," b "] \rightarrow wicket = 1
   else 0
```

- 4) Continuity enforcement
  - Compute ball index: idx(over) = floor(over)
    \*6 + int(10\*(over floor(over)))
  - If previous run was wide/nb (regex r"^\d+(?: w|nb)\$"), expect same idx; else expect idx +1.
  - Skip chunk if expectation not met.
- 5) Collect row
- 6) Build DataFrame from all rows

#### **A.2** Commentary Ground Truth

A sample cricket commentary from our dataset has been shown along with the ground truth that was calculated using the pipeline explained in section 2.2.

- Muzarabani to Tamim, no run fullish ball on middle and leg, clipped to square leg
- Muzarabani to Tamim, no run full and straighter on off this time. Driven down the ground with the full face of the bat
- Muzarabani to Tamim, no run past the outside edge to the batter. Fullish length in the off-stump channel, as Tamim presents his bat playing in the line and the ball shoots of the the pitch
- Muzarabani to Tamim, 1 wide good length ball pitched outside leg, as he shoulders arms. Wide called
- Muzarabani to Tamim, no run fuller on middle and off. He goes across the stumps to clip that to square leg
- Muzarabani to Tamim, no run beaten on the outside edge. Good length delivery pitched on middle and leg, and angles away as he tries to dab at that with an open face
- Muzarabani to Tamim, no run good length again, this time on off. Good bounce for Muzarabani again, as Tamim blocks that off the front foot close to his body

- Chatara to Litton Das, no run full and wide of off to perhaps draw the drive, and angles away further as Liton shoulders arms
- Chatara to Litton Das, no run good length ball on middle and off. Defended off the back foot to cover Two slips in place for Chatara
- Chatara to Litton Das, no run full ball again and closer to off. This was around fifth stump, and Liton was happy to let that go again
- Chatara to Litton Das, no run full length just outside off. Liton takes a good stride forward to tap that to cover
- Chatara to Litton Das, no run fullish length and slightly wide of off. Straightens after pitching after Liton leaves it alone
- Chatara to Litton Das, no run another full delivery just outside off. Defended to cover off the front foot
- Muzarabani to Tamim, no run full length just outside off, and tapped to cover with an open face
- Muzarabani to Tamim, no run pulls his length back a touch just outside off. Driven toward mid-on with the full face of the bat
- Muzarabani to Tamim, FOUR runs slashed on the up through the covers and with a crackling sound. Good length ball outside off, and Tamim takes a solid foot forward to hit that aerially and holds the pose after that too
- Muzarabani to Tamim, no run good length on middle and leg, clipped to square leg off the back foot
- Muzarabani to Tamim, FOUR runs glorious drive between mid-off and cover. Presents the full face of the bat to this full delivery outside off, and gets the second boundary of the over
- Muzarabani to Tamim, no run fullish length outside off, and Tamim plays within the line as the ball passes his outside edge
- Chatara to Litton Das, no run beats him on the outside edge. Fullish, nagging length in the channel with the ball angling away as he tries to defend at that
- Chatara to Litton Das, no run full ball on off again, and defended to point this time
- Chatara to Litton Das, no run goes full but much closer to off stump. Driven to mid-off with the full face of the bat
- Chatara to Litton Das, 1 wide fullish ball pitching on middle and leg, and angling down leg further. Liton shoulders arms, and it's called a wide

Chatara to Litton Das, no run another fullish ball, and straighter as well. Pushed off the front foot to cover

Chatara to Litton Das, FOUR runs flicked off his pads to deep square leg, as the bowler goes full on leg this time. Just clips that to the right of the square leg umpire and beats fine leg to his left

Chatara to Litton Das, no run driven off the full face to point, as Chatara bowls this on a good length and slightly wide of off

Muzarabani to Tamim, no run good carry for Muzarabani off a full length in the offstump channel. Tamim shoulders arms to that, and the keeper collects that really high

Muzarabani to Tamim, 1 run pushes this off the outside edge with his front leg in the air as the bowler goes full and very close to off. Third man rushes to his right to dive and keep that to a single

Muzarabani to Litton Das, no run good length delivery on off, and angling in as he fends that to the on side off his chest

Muzarabani to Litton Das, no run full and on off, as Liton gets a leading edge back to the bowler while trying to flick that to the on side

Muzarabani to Litton Das, no run another full ball on off, and Liton is right forward to block that back

Muzarabani to Litton Das, no run the ball just evades his off stump as he defends this good length ball close to himself. It was angling in after pitching outside off, and Liton played that late with the ball escaping his off stump with a few bounces

Bowler	Balls	Runs	Wickets	Overs	Maidens
Chatara	12	5	0	2.0	1
Muzarabani	18	10	0	3.0	0

Table 6: Bowling summary

Batsman	Runs	Balls_Faced	Fours	Sixes	S/R
Litton Das	4.0	16	1	0	25.0
Tamim	9.0	14	2	0	64.29

Table 7: Batsman Summary

#### **Appendix B: Prompts**

#### **Prompt for Table Generation**

The prompt used for the generating the Batsman and Bowler tables using Zero-Shot (ZS) Chain of Thought (COT) has been shown below. We use ZS COT as it has been shown in (Deng et al., 2024a) that models improve in ZS setting after applying COT. It has also been shown by (Deng et al., 2024a) that few-shot learning does not improve performance and ZS performs far better than fine-tuning setting.

#### **Prompt Card.**

You are an expert in building statistical summary tables from live commentary text. Return ONLY the two JSON objects according to the rules given below - no prose, no code, no markdown.

#### Output rules:

- Two lines total: line 1 = batsman JSON ; line 2 = bowler JSON.
- Use EXACT key casing: batsman, Runs, Balls\_Faced, Fours, Sixes, S/R, dismissal; bowler, Balls, Runs\_Given, Wickets, Overs, Maidens.
- Arrays align by index (e.g., batsman[i ]  $\leftrightarrow$  Runs[i]  $\leftrightarrow$  Balls\_Faced[i], etc.).
- Types: integers for count fields; S/R is a float with two decimals; Overs is "O.B" string (e.g., "3.4").
- Unknown values: use 0 (numbers) or "" (strings). Never output null/NaN.

#### Cricket rules:

#### [Batsman]

- Runs: credit only off-the-bat (exclude byes/leg-byes). For no-balls, bat runs are credited separately; the +1  $\ensuremath{\mathsf{nb}}$  is NOT bat runs.
- Balls\_Faced: increment for every delivery except wides (no-balls DO count as a ball faced).
- Fours/Sixes: set only for off-the-bat boundaries; exclude b/lb boundaries. S/R: (Runs / Balls\_Faced) \* 100,
- rounded to 2 decimals.
- dismissal: "" if not out; else short phrase such as "c Fielder b Bowler" "lbw", "run out", "st", "b Bowler" "hit wicket".

#### [Bowler]

- Balls: count only legal deliveries ( wides/no-balls do NOT add to Balls).
- Runs\_Given: includes all conceded ( incl. wides, no-balls, byes/leg-byes
- Wickets: credit only bowlerattributable dismissals (b, c off bowler, lbw, st off bowler, hit wicket). Do NOT credit run out.

```
- Overs: floor(Balls/6) "." (Balls % 6).
- Maidens: count overs with zero
   Runs_Given in that over (0 if not
    inferable).
Validation:
- Output must be valid JSON with no
   trailing commas and no extra lines.
- Arrays must be equal length per table.
You are about to be given a cricket
    commentary. Extract the final
   batsman and bowler scorecards by
   aggregating across the commentary.
   Return ONLY the two JSON objects as
   specified.
Commentary: {commentary}
Output format (copy keys verbatim;
    replace placeholders with values):
{"batsman":[batsman1,batsman2,...],
 "Runs":[runs1,runs2,...],
 "Balls_Faced":[balls1,balls2,...],
 "Fours":[fours1,fours2,...],
 "Sixes":[sixes1,sixes2,...],
"S/R":[sr1,sr2,...],
"dismissal":[dis1,dis2,...]}
{"bowler":[bowler1,bowler2,...],
 "Balls":[balls_b1,balls_b2,...],
 "Runs_Given":[runs_g1,runs_g2,...],
 "Wickets":[wkts1,wkts2,...],
 "Overs":[overs1,overs2,...],
 "Maidens":[m1,m2,...]}
Let's think step by step.
```

#### C Appendix D: Data Perturbations

We induce three perturbations to study the robustness of the models. Anonymizaion where the named entities for bowler and batsman are replaced by generic placeholders like "Player1", "Player2" and so on. Out of Distribution Entity Substitution that substituted the entities with made up names generated using amalgamation of different names from other sports other than cricket. Entity Entanglement where the role of entities is made difficult to identify. The original commentary has a predictable structure that clearly helps identify the batsman and bowler apart. This perturbation challenges models to have a holistic understanding of the commentary. The examples showing the variation among the original, anonymized, OOD entity substituted and entity entangled has been shown in Table 8.

Original	OOD Entity Sub.	Anon.	Entangle -ment
Muzarabani to Tamim, no run fullish ball on middle and leg, clipped to square leg.	Vinicius Alcaraz to Matt Inge- brigtsen, no run fullish ball on middle and leg, clipped to square leg.	Player3 to Player7, no run fullish ball on middle and leg, clipped to square leg.	Spotlight swings toward Muzara- bani / Tamim; no run fullish ball on middle and leg, clipped to square leg.
Muzarabani to Tamim, no run full and straighter on off this time. Driven down the ground with the full face of the bat.	Vinicius Alcaraz to Matt Inge- brigtsen, no run full and straighter on off this time. Driven down the ground with the full face of the bat.	Player3 to Player7, no run full and straighter on off this time. Driven down the ground with the full face of the bat.	Action with Tamim and Muzara- bani: no run full and straighter on off this time. Driven down the ground with the full face of the bat.
Muzarabani to Tamim, no run past the outside edge to the batter. Fullish length in the off-stump channel, as Tamim presents his bat playing in the line and the ball shoots off the pitch.	Vinicius Alcaraz to Matt Inge- brigtsen, no run past the outside edge to the batter. Fullish length in the off-stump channel, as Matt Inge- brigtsen presents his bat playing in the line and the ball shoots off the pitch.	Player3 to Player7, no run past the outside edge to the batter. Fullish length in the off-stump channel, as Player7 presents his bat playing in the line and the ball shoots off the pitch.	Between Tamim and Muzara- bani: no run past the outside edge to the batter. Fullish length in the off-stump channel, as Tamim presents his bat playing in the line and the ball shoots off the pitch.

Table 8: Comparison of cricket commentary variations across different transformation types. Highlighted text indicates specific differences from the original commentary in terms of entity substitution (player names), structural changes, and semantic modifications.

### D Appendix E: Results Tables

We have done our analysis on two sets of data ODI (50 over match) and T20 IPL (20 over Indian Premiere League). The nature of data is different not only in terms of length but also in other aspects

like recency, T20 data is all from 2025 in contrast to ODI that spans from 2006-2025, the T20 data contains different national players in the same team in contrast to the ODI.

#### **D.1** ODI Innings

For the ODI, we also perform an indepth analysis on the attributes for the batsman and bowler tables. in Table 9, one can see that all models take a hit when asked to form tables without summary, except for Qwen-72B model that shows increase in accuracy for Balls and Overs in Bowler table. In the batsman table, Balls and S/R (Strike Rate) take the biggest hit suggesting that these are the hardest keys in Batsman table. Bowler table does not take that severe hit as a batsman because the summaries are majorly batsman-centric.

#### **D.1.1** Robustness Analysis

We dive deep into the per-key analysis to find the effect of the perturbations on each of the keys as each of them tests the model in a different aspect. We quantified the relative difficulty of different scorecard attributes by applying z-score normalization to model accuracies, a standard technique for comparing features on a common scale. This analysis revealed distinct patterns across batsman and bowler scorecards. For the batsman dimensions, the z-scores were -0.88 (Balls Faced), 0.57 (Fours), -0.41 (Runs), -0.85 (Strike Rate), and 1.57 (Sixes), yielding the difficulty order: Balls Faced > Strike Rate > Runs > Fours > Sixes. In contrast, for the bowler dimensions, the corresponding z-scores were -0.72 (Balls), 1.39 (Maidens), -0.56 (Overs), -0.93 (Runs Given), and 0.82 (Wickets), with the ranking: Runs Given > Balls > Overs > Wickets > Maidens. These results highlight that volumeoriented attributes such as Balls Faced and Runs Given consistently emerge as the most challenging to predict, whereas discrete count-based attributes like Sixes and Maidens are relatively easier, underscoring systematic differences in model reliability across scorecard components.

Gemini's performance increases across almost all the keys for Anonymization and OOD Entity Substitution as shown in Table ??, Llama models (both 70B and 8B) improve their accuracies in Entity Entanglement for the bowler table. The finding highlights that Llama models do not over-rely to surface-level templates on this dataset.

	Witl	n / Witho	out Sumi	nary Cu	es		
Models	]	Batsmar	1	Bowler			
	Cell	Col	Row	Cell	Col	Row	
Gemini 2.5 Flash	91 / 58 -33	52 / 16 -36	84 / 25 -59	80 / 60	52 / 33 -19	51 / 22 -29	
Llama (70b)	83 / 38 -45	14 / 3 -11	75 / 11 -64	51 / 40	30 / 24 -6	2 / 0 -2	
Llama (8b)	83 / 37 -46	13 / 3 -10	75 / 11 -64	52 / 40 -12	30 / 22	4 / 2 -2	
Qwen (72b)	81 / 32 -49	10 / 1 -9	72 / 7 -65	45 / 44	19 / 19 0	1/1	
Qwen (7b)	64 / 15 -49	1 / 0 -1	39 / 1 -38	27 / 26	13 / 11	0/0	
GPT 40 mini	80 / 27 -53	8 / 0 -8	70 / 4 -66	49 / 46	14 / 14	1/1	

Table 11: Comparison of model performance at the table level when summary cues are provided / omitted within T20 innings

#### D.2 T20 Innings

The table level metrics in T20 has a much higher accuracy compared to ODI due to shorter matches and context length. The results have been shown in Table 12. An interesting trend emerges in the T20 setting: across all models, bowler tables achieve higher accuracy than batsman tables when explicit summary cues are absent. This behavior contrasts with the ODI data, where batsman tables generally dominate. The shift suggests that in shorter formats, the temporal demands on the model are inherently lower—bowling spells are shorter, cues are denser, and fewer overs need to be tracked. As a result, the aggregation burden is reduced, allowing models to maintain consistency more effectively. This highlights a format-sensitivity in LLM reasoning, where compact temporal horizons (T20) favor bowlers, while extended horizons (ODI) expose challenges in sustaining long-form state tracking.

The key-level metrics for with/without summary cues reveal a consistent trend across all models: batsman tables are highly cue-dependent, while bowler tables remain relatively more stable. For batsmen, the removal of summary lines results in dramatic accuracy drops, often in the range of 50 to -65 points across core metrics such as Runs, Balls Faced, and Strike Rate.

In contrast, bowler scorecards exhibit greater robustness to the removal of summaries. While some deflection is observed (e.g., -18 for LLaMA, -23 for Gemini in Runs Given), the magnitudes are

				With / Wi	thout Sum	mary Cues	3			
Models			Batsman					Bowler		
	Balls	4s	Runs	S/R	6s	Balls	Maidens	Overs	Runs	Wickets
Gemini 2.5 Flash	85 / 21 -64	92 / 71 -21	88 / 39 -49	83 / 21 -62	98 / 91 -7	35 / 19 -16	86 / 84 -2	40 / 22 -18	25 / 17 -8	23 / 25 +2
LLaMA (70B)	82 / 15 -67	88 / 55 -33	85 / 30 -55	82 / 15 -67	95 / 81 -14	18 / 18	77 / 75 -2	19 / 18 -1	9 / 8 -1	83 / 66 -17
Qwen (72B)	82 / 10 -72	85 / 50 -35	83 / 18 -65	81 / 11 -70	95 / 82 -13	16 / 24 +8	74 / 72 -2	17 / 24 +7	4 / 4 0	76 / 67 -9
LLaMA (8B)	83 / 16 -67	89 / 55 -34	85 / 30 -55	82 / 15 -67	95 / 80 -15	18 / 18	77 / 74 -3	19 / 18 -1	8/8	85 / 65 -20
Qwen (7B)	73 / 4 -69	65 / 33 -32	70 / 12 -58	69 / 7 -62	80 / 64 -16	1/1	75 / 73 -2	1/2+1	2/2	28 / 25 -3
GPT 40-Mini	80 / 7 -73	85 / 39 -46	82 / 17 -65	79 / 8 -71	92 / 72 -20	5 / 4	75 / 75 0	23 / 24	6/7 -1	64 / 51 -13

Table 9: Comparison of model performance on Batsman and Bowler scorecard generation in the zero-shot (ZS) Chain of Thought (COT) setting. Batsman evaluation includes key metrics such as Balls Faced (Balls), Fours (4s), Runs Scored (Runs), Strike Rate (S/R), and Sixes (6s), while Bowler evaluation covers Balls Bowled (Balls), Maiden Overs (Maidens), Overs Bowled (Overs), Runs Conceded (Runs), and Wickets Taken (Wickets).

significantly smaller than for batsman metrics.

Within this broader pattern, Qwen-7B presents an especially interesting case. Despite low absolute accuracy on bowling metrics (e.g., Wickets 26–29), it shows virtually no deflection between with- and without-summary conditions (+0 to +3 across most metrics). This suggests that Qwen-7B does not meaningfully exploit summary cues for bowling reconstruction, instead relying almost entirely on incremental aggregation from the commentary stream. In contrast, larger models such as Gemini or LLaMA partially benefit from summaries and thus register moderate declines when these are removed.

In the T20 setting, perturbation analysis highlights that bowler tables are generally more resilient than batsman tables. The results are shown in Table 13, though model behaviors diverge in revealing ways. Under Anonymization, both Gemini and LLaMA families show only small declines, while Qwen models—particularly Qwen-7B-remain essentially flat for bowlers, suggesting they aggregate over incremental evidence rather than depend on surface identity cues. Out-of-distribution entity substitution, however, exposes a weakness: Qwen-72B collapses sharply on bowler Balls and Overs (-29%), indicating fragile entity resolution when names fall outside training distribution, whereas Gemini and LLaMA retain stability by relying on local lexical patterns. In contrast, Entity Entanglement produces large, sometimes spurious gains

for Gemini and LLaMA in bowler metrics, consistent with over-merging tracks when identity boundaries blur; Qwen models instead degrade modestly, reflecting their dependence on distributed aggregation rather than shortcutting through collapsed entities.

#### **D.2.1** Distributional Robustness

We do the same analysis for T20 data as we did for the ODI in 5, to check the effect of each perturbations on the models and see if the ranking of robust LLMs changes on T20 data.

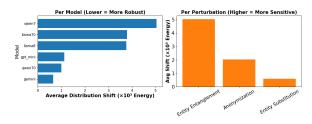


Figure 5: Comparison of avg. distribution shifts across models (left) and perturbation types (right). Lower shift values indicate higher robustness.

The results in Figure 5 highlights two complementary perspectives on robustness and sensitivity. On the left, per-model analysis shows that smaller average distribution shifts indicate greater robustness. Here, Gemini and Qwen-70B exhibit the lowest shifts, suggesting they are the most stable, while LLaMA-8B, LLaMA-70B, and Qwen-7B dis-

			`	With / Wi	thout Sun	mary Cu	es			
Models			Batsman					Bowler		
	Balls	4s	Runs	S/R	6s	Balls	Maidens	Overs	Runs	Wickets
Gemini 2.5 Flash	87 / 30 -57	96 / 87 -9	91 / 52 -39	86 / 29 -57	97 / 93 -4	68 / 34 -34	100 / 100	77 / 40 -37	60 / 37 -23	96 / 92 -4
LLaMA (70B)	79 / 19 -60	89 / 58 -31	80 / 24 -56	78 / 15 -63	91 / 73 -18	33 / 15	100 / 100	33 / 15 -18	5 / 3 -2	83 / 66 -17
Qwen (72B)	79 / 15 -64	83 / 48 -35	78 / 18 -60	76 / 12 -64	89 / 64 -25	24 / 26 +2	<b>99 / 99</b> 0	25 / 26 +1	4 / 3 -1	75 / 69 -6
LLaMA (8B)	79 / 20 -59	89 / 57 -32	80 / 23 -57	78 / 15 -63	92 / 71 -21	35 / 14	100 / 99 -1	35 / 14 -21	7 / 4 -3	84 / 67 -17
Qwen (7B)	68 / 5 -63	60 / 21 -39	64 / 7 -57	61 / 4 -57	68 / 38 -30	2/2	100 / 99 -1	3 / 4 +1	2/2	26 / 29 +3
GPT 40 mini	80 / 13 -67	83 / 39 -44	77 / 15 -62	77 / 9 -68	85 / 59 -26	26 / 27 +1	99 / 99 0	<b>44 / 44</b> 0	5 / 5 0	70 / 56 -14

Table 12: Comparison of model performance at the key level when summary cues are provided / omitted within commentary of T20 innings

play substantially larger shifts, marking them as the most sensitive. On the right, the per-perturbation analysis reveals that Entity Entanglement induces the highest average shift across models, making it the most disruptive perturbation, followed by Anonymization and then Entity Substitution, which has the smallest effect overall. Together, the plots demonstrate that robustness varies widely across models, but across perturbation types, entity entanglement consistently drives the strongest distributional drift.

#### **E** Experiment Details

In this section we describe the computational resources for every model. For Gemini<sup>7</sup> and GPT-40 mini<sup>8</sup> we used their sdk packages. For Open Source models like Qwen and Llama we used DeepInfra<sup>9</sup>.

<sup>&</sup>lt;sup>7</sup>https://aistudio.google.com/

<sup>&</sup>lt;sup>8</sup>https://chatgpt.com

<sup>9</sup>https://deepinfra.com/

			Ano	nymizatio	n (Original	/ Anonym	nized)			
Models			Batsman					Bowler		
	Balls	4s	Runs	S/R	6s	Balls	Maidens	Overs	Runs	Wickets
Gemini 2.5 Flash	37 / 35	88 / 86 -2	58 / 56 -2	36 / 35 -1	95 / 94 -1	52 / 51	99 / 99 0	57 / 54 -3	51 / 51	96 / 94 -2
LLaMA (70b)	20 / 17	55 / 50 -5	24 / 20 -4	15 / 14 -1	73 / 69 -4	8/6	100 / 100	9 / 6 -3	3 / 2	75 / 67 -8
QWEN (72b)	15 / 14 -1	50 / 45 -5	15 / 13 -2	12 / 9 -3	70 / 65 -5	36 / 31 -5	99 / 100 +1	37 / 35 -2	6/6 0	81 / 76 -5
LLaMA (8b)	19 / 17 -2	55 / 50 -5	23 / 19	15 / 13 -2	71 / 69 -2	8/5	100 / 100	8 / 5 -3	2/2	75 / 67 -8
QWEN (7b)	3/2	21 / 17	5 / 4 -1	2/2	40 / 33 -7	3 / 1	99 / 99 0	6 / 2 -4	2 / 1 -1	41 / 33
GPT 40 mini	13 / 12	37 / 38 +1	15 / 13 -2	9 / 8 -1	63 / 60	14 / 10	99 / 99 0	28 / 28	4 / 3 -1	67 / 61 -6
OOD Entity Substitution (Original / Entity subs)										
Models			Batsman					Bowler		
	Balls	4s	Runs	S/R	6s	Balls	Maidens	Overs	Runs	Wickets
Gemini 2.5 Flash	37 / 33	88 / 87 -1	58 / 55 -3	36 / 34 -2	95 / 94 -1	52 / 51	99 / 99 0	57 / 54 -3	51 / 52 +1	96 / 95 -1
LLaMA (70b)	20/20	55 / 57 +2	24 / 22 -2	15 / 15 0	73 / 71 -2	8/5	100 / 100	9 / 5 -4	3 / 2 -1	75 / 73 -2
QWEN (72b)	15 / 14 -1	50 / 50 0	15 / 15 0	12 / 11 -1	70 / 72 +2	37 / 8 -29	99 / 97 -2	38 / 9 -29	6 / 1 -5	80 / 68 -12
LLaMA (8b)	19 / 20	55 / 58 +3	23 / 23	15 / 15 0	71 / 73 +2	8/6	100 / 100	8 / 6 -2	2/2	75 / 73 -2
QWEN (7b)	3/3	21 / 21	5 / 7 +2	2/2	40 / 38 -2	3/1 -2	99 / 100 +1	6/3 -3	2 / 1 -1	41 / 36 -5
GPT 40 mini	13 / 12	37 / 38 +1	15 / 14 -1	9 / 8 -1	63 / 64 +1	14 / 11	99 / 99 0	28 / 27 -1	4/4	67 / 63 -4
			Entity	Entangle	ment (Orig	ginal / Enta	ingled)			
Models			Batsman					Bowler		
	Balls	4s	Runs	S/R	6s	Balls	Maidens	Overs	Runs	Wickets
Gemini 2.5 Flash	37 / 61 +24	88 / 91 +3	58 / 73 +15	36 / 57 +21	95 / 95 0	52 / 71 +19	99 / 99 0	57 / 79 +22	51 / 64 +13	96 / 96 0
LLaMA (70b)	20 / 13	55 / 44 -11	24 / 15 -9	15 / 10 -5	73 / 63 -10	8 / 28 +20	100 / 100	9 / 28 +19	3/3	75 / 76 +1
QWEN (72b)	15 / 9 -6	50 / 42 -8	15 / 10 -5	12 / 7 -5	70 / 63 -7	36 / 29	99 / 99 0	37 / 31 -6	6 / 5 -1	81 / 74 -7
LLaMA (8b)	19 / 12 -7	55 / 44 -11	23 / 16 -7	15 / 10 -5	71 / 61 -10	8 / 28 +20	100 / 100	8 / 28 +20	2/3 +1	75 / 77 +2
QWEN (7b)	3/2	21 / 16 -5	5 / 6 +1	2/3 +1	40 / 37 -3	3/2	99 / 99 0	6/3 -3	2 / 1 -1	41 / 37 -4
GPT 40 mini	13 / 9	37 / 33 -4	15 / 11 -4	9 / 6 -3	63 / 56 -7	14 / 26 +12	99 / 99 0	28 / 36 +8	4/4	67 / 65 -2

Table 13: Comparison of model performance at the key level across different data perturbations on T20 innings