HARNESSING TEMPORAL DATABASES FOR SYSTEMATIC EVALUATION OF FACTUAL TIME-SENSITIVE QUESTION-ANSWERING IN LLMS

Anonymous authors
Paper under double-blind review

ABSTRACT

Facts change over time, making it essential for Large Language Models (LLMs) to handle time-sensitive factual knowledge accurately and reliably. Although factual Time-Sensitive Question-Answering (TSQA) tasks have been widely developed, existing benchmarks often face manual bottlenecks that limit scalable and comprehensive TSQA evaluation. To address this issue, we propose TDBench, a new benchmark that systematically constructs TSQA pairs by harnessing temporal databases and database techniques, such as temporal functional dependencies, temporal SQL, and temporal joins. We also introduce a new evaluation metric called time accuracy, which assesses the validity of time references in model explanations alongside traditional answer accuracy for a more fine-grained TSQA evaluation. Extensive experiments on contemporary LLMs show how TDBench enables scalable and comprehensive TSQA evaluation while reducing the reliance on human labor, complementing current TSQA evaluation approaches that largely center on Wikipedia/Wikidata by enabling LLM evaluation on application-specific data.

1 INTRODUCTION

Facts are not static – they evolve over time (Jensen et al., 1996). As Large Language Models (LLMs) are increasingly integrated into real-world applications (Jiao et al., 2024), their abilities to manage time-sensitive factual knowledge have become crucial for ensuring both accuracy and reliability (Yuan et al., 2024). For example, when asked, "Who is the current president of the U.S.?", an LLM must accurately distinguish between past and present presidents to avoid providing outdated or incorrect responses, which can mislead users and undermine trust (Huang et al., 2024).

To assess LLMs' abilities to handle time-sensitive factual knowledge, many Time-Sensitive Question Answering (TSQA) benchmarks have been developed (Chen et al., 2021; Dhingra et al., 2022; Kasai et al., 2023; Tan et al., 2023; Vu et al., 2023; Kim et al., 2024; Zhao et al., 2024; Zhu et al., 2025). These benchmarks primarily assess two LLM capabilities: (1) *temporal reasoning*, the ability to understand various temporal contexts within questions (e.g., "before 2019", "during the 5th Winter Olympics") and (2) *temporal alignment*, the ability to provide answers that reflect current factual knowledge in the real world (e.g., being aware of the current president).

However, existing factual TSQA benchmarks often lack a systematic design, relying heavily on manual efforts for benchmark construction and maintenance. Assessing temporal reasoning ability requires creating diverse temporal contexts such as "before 2019" or "during the 5th Winter Olympics", which typically relies on human writers (Kasai et al., 2023; Wei et al., 2023; Vu et al., 2023). Using predefined question templates can automate part of this process (e.g., "before `[YEAR]`"), but it still requires human efforts to design templates and often uses a small, fixed set that compromises diversity (e.g., 9 templates used in Dhingra et al. (2022), 16 used in Margatina et al. (2023); see more details in Sec. 5). In addition, the evolving nature of time-sensitive knowledge requires continual updates of TSQA benchmarks, posing a benchmark maintenance challenge. For instance, RealTimeQA (Kasai et al., 2023) manually curated weekly news (e.g., CNN) to incorporate new world facts, but updates have recently ceased due to the high costs of manual curation (Uddin et al., 2024).

To tackle these manual bottlenecks, we propose **TDBench**, a benchmarking framework designed for a more systematic TSQA evaluation. Unlike existing TSQA benchmarks, TDBench eliminates the

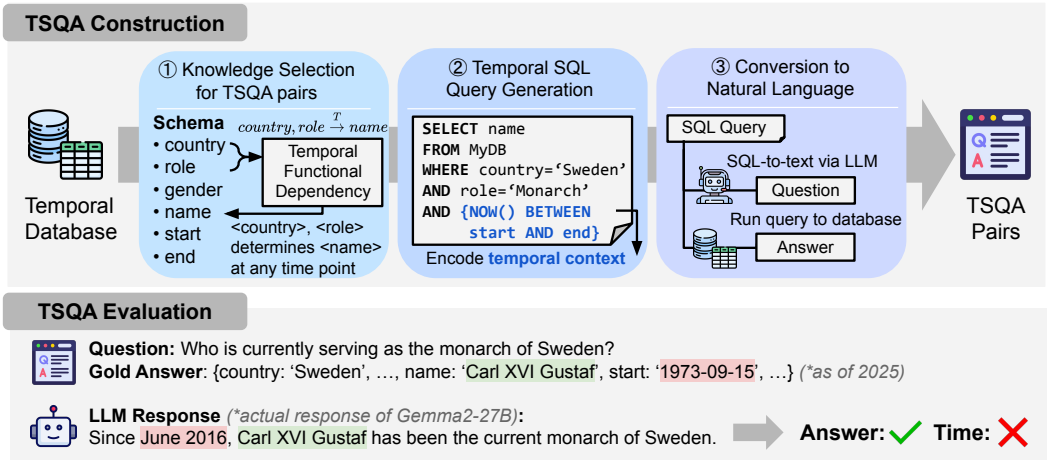


Figure 1: Overview of TDBench framework. TDBench systematically constructs Time-Sensitive QA (TSQA) pairs by (1) selecting factual knowledge via temporal functional dependencies, (2) generating temporal SQL queries with diverse temporal contexts, and (3) converting queries into natural language QA pairs using an LLM and the database. During evaluation, TDBench automatically verifies both the final answer and time references in LLM responses, capturing cases where the model hallucinates in the explanation despite providing the correct answer. TDBench supports diverse TSQA scenarios, including temporal alignment and temporal reasoning tasks – see more framework details in Sec. 3.

need for human labor in designing temporal contexts or question templates. Instead, TSQA pairs are automatically generated from an input data source, namely, *temporal databases* – extensions of conventional databases that are well-established for managing time-sensitive knowledge (Jensen et al., 1996). These temporal databases can be user-defined or sourced from general platforms like Wikipedia, allowing users to flexibly construct TSQA benchmarks based on their own interests.

Our key idea is to utilize database techniques such as *Temporal Functional Dependencies* (TFDs), *temporal Structured Query Language* (SQL), and *temporal joins* for automatic TSQA construction. As shown in Fig. 1, TDBench framework proceeds in three steps: (1) selecting factual knowledge via TFDs, which pinpoint attributes whose values can be uniquely determined at any timepoint (e.g., a name of a country's president) and thus can be suitable for the TSQA task; (2) generating temporal SQL queries via temporal SQL operators (e.g., `BETWEEN`, `DATEDIFF`), which encodes various temporal contexts based on 13 mutually exclusive and exhaustive temporal relations (Allen, 1983); and (3) translating SQL queries into natural language QA pairs using an LLM and the database. Through these steps, TDBench automates TSQA construction and simplifies maintenance; updating the underlying database automatically refreshes the generated QA pairs. We also show how temporal joins increase TSQA complexity by generating implicit temporal contexts (e.g., "during the 5th Winter Olympics"), which can test LLMs' advanced reasoning abilities such as event–event reasoning (Tan et al., 2023), while eliminating the need of additional manual curation (Tan et al., 2023).

Alongside the QA construction, we introduce a new metric called *time accuracy* to support a more fine-grained TSQA evaluation. During QA tasks, LLMs can often hallucinate in explanations while providing correct answers (Ji et al., 2023; Oh et al., 2024). We find this phenomenon manifests in TSQA tasks as inaccurate time references, as illustrated in Fig. 1; a model correctly identifies the current monarch of Sweden, but hallucinates his start date. Since traditional answer-only evaluations cannot capture such errors, we use time accuracy to verify the validity of time references as well as final answers, enabling automatic verification with SQL-based temporal constraints.

Extensive experiments demonstrate how TDBench enables a scalable and comprehensive TSQA evaluation while reducing human labor. We assess several popular LLMs – GPT-3.5 (OpenAI, 2022), GPT-4 (OpenAI, 2023), GPT-4o (OpenAI, 2024), Llama3.1-70B (Dubey et al., 2024), Mixtral-8x7B (Jiang et al., 2024), Gemma2-27B (Team et al., 2024), Qwen2-72B (Bai et al., 2023), and Granite3.1-8B (Granite Team, 2024) – across various TSQA tasks, including temporal alignment, temporal reasoning, and multi-hop settings with implicit temporal contexts. By leveraging TDBench's generalization to arbitrary domains, we move beyond the previous Wikipedia/Wikidata-centric TSQA evaluation and uncover LLM performances in application-specific domains (e.g., medical, legal),

which can fall outside the scope of public platforms. In addition, our time accuracy metric reveals that LLMs largely hallucinate on time references despite providing correct answers, where the accuracy of both the answer and time references is on average 21.7% lower than just answer accuracy in our experiments. Diverse SQL-generated temporal contexts highlight specific weaknesses in understanding temporal constraints (e.g., LLMs underperforming for 'finish' compared to 'start'), identifying LLMs' temporal blind spots that are not clearly observed in other benchmarks.

Summary of Contributions (1) We propose TDBench, a new benchmark that systematically constructs TSQA pairs by harnessing temporal databases and database techniques. (2) We emphasize the need for assessing model explanations, introducing time accuracy to capture invalid time references for more reliable TSQA evaluation. (3) We conduct extensive experiments on contemporary LLMs, demonstrating how TDBench enables a scalable and comprehensive evaluation while reducing human labor and complements existing TSQA approaches centered on Wikipedia/Wikidata.

2 BACKGROUNDS

Temporal Database Temporal databases (Jensen & Snodgrass, 2018) extend conventional relational databases with the concept of time. Both types of databases store *structured* data, where information is organized into a fixed schema with predefined attributes (i.e., columns) and corresponding values (i.e., rows or tuples). While conventional relational databases typically retain only the latest state of each entity, temporal databases are specifically designed to capture time-varying information by storing historical states with associated timestamp attributes. In this work, we focus on temporal databases following the *uni-temporal* data model, which stores the valid time interval of each row using two timestamp attributes (e.g., *start* and *end* in Table 1). We demonstrate how the structured nature of these temporal databases enables systematic time-sensitive question generation by explicitly tracking when facts hold true.

Table 1: An example temporal database *Leader(country, role, name, gender, start, end)*.

country	role	gender	name	start	end
USA	President	M	Bush	2001	2009
USA	President	M	Obama	2009	2017
U.K.	Monarch	F	Elizabeth	1952	2022

Temporal Functional Dependency and Join Temporal databases possess two unique properties: 1) *temporal functional dependencies* (TFDs) and 2) *temporal joins*. TFDs generalize functional dependencies (FDs) defined in conventional databases[1], which denote relationships between two sets of attributes X and Y where the X values determine the Y values (i.e., $X \rightarrow Y$). TFDs extend this notion with a time dimension, requiring the dependency to hold at every timepoint (i.e., $X \xrightarrow{T} Y$; Jensen et al. (1996)). For instance, *country, role* $\xrightarrow{T}$ *name* holds in Table 1, which ensures that each country has a unique role-holder at any given year. Temporal joins similarly incorporate time when combining two or more tables. We mainly focus on temporal natural joins, which only join tuples with overlapping validity intervals. In the following sections, we leverage these properties to effectively evaluate LLM responses. Formal definitions of both properties are presented in Sec. A.

3 TDBENCH

We introduce TDBench, a benchmarking framework for systematic Time-Sensitive Question-Answering (TSQA) evaluation. We first explain the QA construction process (Sec. 3.1), which automatically generates TSQA pairs given an input temporal database to address manual bottlenecks in benchmark construction and maintenance. We then explain the evaluation process (Sec. 3.2), introducing a newly proposed metric called time accuracy for a more fine-grained TSQA evaluation. We finally discuss how to increase TSQA complexity by generating implicit temporal contexts (Sec. 3.3).

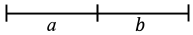
3.1 QA CONSTRUCTION

Our key idea is to harness temporal database techniques to systematize the QA construction process. As shown in Fig. 1, TDBench proceeds in the following three steps, yielding several benefits.

① **Knowledge Selection for TSQA Pairs** Given a temporal database, we use Temporal Functional Dependencies (TFDs; Sec. 2) to automatically select attribute sets for constructing TSQA pairs.

[1]FD and TFDs are defined by the database owner. These properties are typically imposed in databases to help identify data inconsistencies and improve data integrity (Jensen et al., 1996).

Table 2: Illustration of the *meet* relation between temporal intervals a and b, from which we generate the SQL condition and temporal context. Diverse temporal contexts can be constructed by sampling different values for a and b. In this example, a denotes a president's term, and *March 20, 2001* and *half a year* correspond to b.end and b.length, respectively. See Table 10 for all 13 temporal relations.

Relation	Interval Diagram	SQL Condition	Example Temporal Context
a meet b		a.end = b.end - b.length	A president who ends exactly *half a year* before *March 20, 2001*

Given a TFD $X \xrightarrow{T} Y$ satisfied in a database relation r, we specify $r.X$ values in the question and use the corresponding $r.Y$ values as the answers, since X values determine Y values at any time by the TFD definition. For example, $country, role \xrightarrow{T} name$ leads to the question "Who is the [role] of the country [country]"? with the answer [name], where [role], [country], and [name] are placeholders for attribute values. As TFDs are part of the design theory of temporal databases, this FD-based logic generalizes to arbitrary schemas of temporal databases, enabling systematic knowledge selection.

② **Temporal SQL Query Generation** We propose the `Genqueries` algorithm to generate temporal Structured Query Language (SQL) queries using the TFD-selected attributes. SQL is used to interact with databases to manage and query data. Rather than directly generating natural language questions, generating questions via temporal SQL queries allows us to utilize built-in temporal operators, reducing the manual effort to design temporal contexts. `Genqueries` first (1) builds a base query using the TFD-selected attributes and then (2) adds temporal constraints, as shown in Fig. 1. For (1), the X attributes are used in the `WHERE` clause for the question, and the Y attributes are used in the `SELECT` clause for the answer (e.g., $country, role \xrightarrow{T} name$ yields `SELECT name WHERE country='USA' AND role='president'`). For (2), SQL conditions are generated based on 13 mutually exclusive and exhaustive temporal relations from the database literature (Allen, 1983) – *before, after, meet, met-by, overlap, overlapped-by, equal, start, started-by, finish, finished-by, during*, and *contains*. For example, Table 2 shows the temporal SQL condition and the temporal context corresponding to the *meet* relation, where a time interval a ends exactly when a time interval b starts. The resulting temporal condition is appended to the base query as a temporal constraint. We present the full set of SQL conditions and the pseudocode of `Genqueries` in Sec. B.

③ **Conversion to Natural Language QA Pairs** We convert the generated queries into natural language QA pairs by using an LLM and the underlying database. For questions, we use GPT-4o (OpenAI, 2024) as an SQL-to-text translator via system prompts, which we observe to achieve 91.5% accuracy in our setup based on LLMs' strong zero-shot performance in SQL-to-text tasks (Zhang et al., 2024a) – see detailed setups (e.g., actual prompt and temperature) and error analyses in Sec. B.3. For answers, we simply run the generated SQL queries on the database. In this way, we obtain linguistically diverse questions from an LLM while ensuring that the answers follow the underlying database, as shown in Table 3. We show more examples of generated QA pairs in Sec. B.3.

Benefits Compared to prior approaches, TDBench offers many benefits by harnessing both database techniques and LLMs for QA construction. Using TFDs in step ① enables dynamic benchmarking that is also convenient, eliminating the need for manual data pre-processing to identify time-related attributes (Gupta et al., 2023; Zhao et al., 2024). Using temporal SQL in step ② eliminates the human labor to write customized, domain-specific templates while expanding time constraints to the full set of 13 interval relations, instead of the typically used 4-6 types (mainly "in [year]", "from [year1] to [year2]", "before", and "after" (Chen et al., 2021; Dhingra et al., 2022)). Lastly, we demonstrate how step ③ (i.e., LLM-generated questions, DB-grounded answers) greatly reduces hallucination and inference costs compared to LLM-only approaches (Kim et al., 2024) – see more details in Sec. D.8.

3.2 Evaluation

Using the generated QA pairs, TDBench evaluates not only final answers via traditional answer accuracy, but also explanations via a newly proposed time accuracy metric to offer a fine-grained TSQA evaluation. We explain the definition and the verification of the proposed time accuracy metric, along with the various TSQA evaluation scenarios supported by TDBench.

Definition of Time Accuracy We define time accuracy as the correctness of *time references* – specifically the start and end dates in our setup – that serve as rationales for temporal reasoning

Table 3: A single SQL query generates multiple QA pairs by translating into diverse natural language questions with the same answer. To evaluate both answer and time accuracy, the SQL query also outputs a relation-specific time reference (e.g., `end` for the 'meet' relation), defined in Table 10.

SQL Query (relation='meet')	**Generated QA**
`SELECT name, end FROM Leader WHERE Country='Brazil' AND Role='President' AND date(end) = date('2019-05-01', '-4 month')`	**[Questions]** "Who was the president of Brazil whose term ended exactly four months before May 1, 2019?", "Can you provide the president of Brazil who finished their term four months prior to May 1, 2019?"... **[Answer]** Michel Temer **[Time reference]** 2019-01-01 (end)
[Model Response] The answer is *Michel Temer* (answer), whose term ended in *January 1, 2019* (time reference).	

required in a time-sensitive question. For example, the questions in Table 3 require reasoning over the president's end date, where the model should mention "January 1, 2019" in the explanation given the constraint "four months before May 1, 2019". If a question requires both a start and an end date, but the model gets only one correct, the time accuracy is 50%. See the formal definition in Sec. B.4.

Verification of Time Accuracy TDBench supports automatic verification of time accuracy by utilizing the SQL-generated temporal constraints, which explicitly encode the temporal reasoning logic (e.g., "date(end) = date('2019-05-01'), -4 month" in Table 3 indicates that the end date is required for reasoning). We thus define relation-specific criteria that specifies which time references to verify: start date for 'after', 'met-by', 'started-by', end date for 'before', 'meet', 'finished-by', and both dates for the remaining seven relations, as summarized in Table 10. To facilitate evaluation, we prompt target LLMs to explicitly state time references used in their reasoning during the TSQA task. Since model responses may include unrelated time information (e.g., "As of 2025, the answer is..."), we employ an LLM-based judge rather than exact matching to verify time references, achieving 91.1% accuracy under manual inspection – see more details and error analyses in Sec. B.5. We also demonstrate how the time accuracy metric can be supported in other TSQA benchmarks in Sec. 4.1.

Evaluation Scenarios TDBench supports various TSQA evaluation scenarios: (1) evaluation of *temporal alignment*, which tests whether the LLM is up-to-date with current world knowledge. As this scenario grounds questions to a temporal constraint "current," we use only the "overlap" relation in `Genqueries` (Table 10); (2) evaluation of *temporal reasoning*, which assesses the LLM's understanding of diverse temporal contexts, where we use all 13 interval relations in `Genqueries`; (3) evaluation of *open-book/closed-book settings*, which differs by the presence of additional context that can aid the QA task. In the open-book setting, we append both relevant and irrelevant rows from the database to the question, whereas such context is removed in the closed-book setting (see Sec. B.6 for an example QA). We note that these scenarios are enabled by the expressiveness of temporal SQL, which also allows natural extensions to broader scenarios – see how to extend `Genqueries` to incorporate non-temporal data attributes or other tasks such as event-counting in Sec. B.2.

3.3 Extension with Implicit Temporal Contexts

We can further increase the complexity of the generated questions by performing *temporal joins* (Sec. 2) of tables within the SQL queries. In particular, temporal joins induce implicit event-event reasoning (Tan et al., 2023) that requires models to identify two or more temporally overlapping events. For example, performing a temporal join between *Leaders(country, role, gender, name, start, end)* and *Olympic(country, city, game_edition, start, end)* on the common column '*country*' pairs Olympic host countries with their national leaders at that time, where a question such as "q_1*: Who was the president of the host country during the 1988 Summer Olympics?*" can be generated. TDBench naturally extends from single tables to joined tables and can generate such questions, since TFDs in the joined table can be derived via standard FD and TFD inference rules (Jensen et al., 1996); for example, $game\_edition \rightarrow country$ (in *Olympic*) and TFD $country, role \xrightarrow{T} name$ (in *Leader*) yields a new TFD $game\_edition, role \xrightarrow{T} name$, which can be converted to q_1 via `Genqueries`. The verification process is the same as that for single-table questions. While other, more complex implicit temporal contexts could be constructed, we emphasize that TDBench offers an automatic way to generate these implicit contexts – moving beyond prior work that typically relies on manual construction (Tan et al., 2023; Wei et al., 2023; Wu et al., 2024; Jia et al., 2024).

Table 4: Performance evaluation of eight LLMs on the temporal alignment TSQA task. We report the proportion of correct responses under two evaluation settings: answer-only (**A**) and answer and time (**AT**), along with their difference (Δ = **A**−**AT**). Wikipedia results are reported in aggregate, and domain-specific results are broken down by subdomain. Best results are shown in bold.

	Wikipedia			Law			Carbon Tax			Heritage			Netflix		
Model	**A**	**AT**	Δ	**A**	**AT**	Δ	**A**	**AT**	Δ	**A**	**AT**	Δ	**A**	**AT**	Δ
GPT-3.5	47.5	22.4	25.1	84.3	39.9	44.3	19.9	8.4	11.4	62.7	26.5	36.2	29.3	19.1	10.1
GPT-4	44.5	29.6	14.9	82.4	52.3	**30.0**	32.0	23.9	**8.1**	74.5	44.5	30.0	32.4	26.4	6.1
GPT-4o	**73.9**	48.8	25.1	84.3	**54.0**	30.3	72.1	**43.1**	29.0	72.5	**53.3**	19.2	32.9	25.9	7.0
Llama3.1-70B	64.6	**56.7**	**7.9**	84.6	44.9	39.7	57.6	39.7	17.8	**75.5**	39.7	35.8	35.6	**28.6**	7.0
Mixtral-8x7B	42.9	30.9	12.0	74.1	42.2	32.0	28.3	16.5	11.8	35.6	18.1	**17.5**	20.7	17.1	3.6
Gemma2-27B	69.3	32.8	36.5	84.3	29.8	54.6	**73.1**	25.2	47.8	69.2	22.0	47.2	**36.0**	27.7	8.3
Qwen2-72B	62.7	34.1	28.6	84.0	34.2	49.9	57.2	27.6	29.6	53.5	20.2	33.3	22.5	19.4	**3.1**
Granite3.1-8B	49.6	26.1	23.5	**90.1**	28.6	61.4	45.1	0.0	45.1	42.0	4.5	37.5	19.6	14.9	4.7
Average	56.9	35.2	21.7	83.5	40.7	42.8	48.2	23.1	25.1	60.7	28.6	32.1	28.6	22.4	6.2

4 EXPERIMENTS

We perform extensive experiments to demonstrate how TDBench enables diverse and fine-grained temporal evaluation of LLMs. More detailed settings (e.g., system prompts) are provided in Sec. C.

LLMs Compared We compare GPT-3.5 (OpenAI, 2022), GPT-4 (OpenAI, 2023), GPT-4o (OpenAI, 2024), Llama3.1-70B (Dubey et al., 2024), Mixtral-8x7B (Jiang et al., 2024), Gemma2-27B (Team et al., 2024), Qwen2-72B (Bai et al., 2023), and Granite3.1-8B (Granite Team, 2024). We set all the temperature parameters to zero to exclude randomness in the LLM responses.

Datasets We use temporal databases from two types of sources: (1) Wikipedia covering domains such as *Countries*, *Athletes*, *Organizations*, and *Olympics*, which are commonly addressed in existing TSQA benchmarks (Chen et al., 2021; Dhingra et al., 2022; Mousavi et al., 2024), generating 6,177 questions; and (2) other platforms such as Kaggle, covering areas including same-sex marriage laws, carbon taxation, UNESCO heritage, and Netflix shows to model domain-specific scenarios in *Legal*, *Environmental*, *Cultural*, and *Social* contexts, generating 1,704 questions. More details on datasets, including schemas, used TFDs, and subcategories of questions, are provided in Sec. C.2.

Performance Measures We mainly use the following three performance evaluation metrics.

- *Answer accuracy* (**A**): Portion of responses with correct answers.
- *Time accuracy* (**T**): Portion of responses with correct time references, evaluated using relation-specific criteria (Table 10). If two time references are expected (e.g., start and end dates), partial credit (50%) is given when only one is correct. Granularity (e.g., year, month) varies by dataset.
- *Answer-Time accuracy* (**AT**): Portion of responses with both correct answers and time references. Here, we do not give partial credit (i.e., only consider 100%) when evaluating time accuracy.

4.1 EVALUATION OF TEMPORAL ALIGNMENT

We evaluate the temporal alignment of LLMs, assessing the ability to answer up-to-date questions that reflect current world knowledge (Dhingra et al., 2022; Kasai et al., 2023; Mousavi et al., 2024).

Performance Variations when Accounting for Time Accuracy Table 4 shows notable performance variations across domains under two evaluation settings: **A** (answer-only) and **AT** (answer and time). While the models generally achieve high **A** by retrieving correct up-to-date answers, they often fail to generate accurate time references, resulting in a 21.7% average performance drop in **AT** on the Wikipedia dataset. This gap reveals the limitation of traditional answer-only evaluation, indicating that a large portion of factually inconsistent responses with incorrect time references can be overlooked – see actual cases in Sec. D.1. We also observe domain-specific LLM performances; GPT-4o performs best in domains such as law, carbon tax, and UNESCO heritage, while Llama3.1-70B excels in the Netflix domain – demonstrating TDBench's applicability beyond Wikipedia-based data.

Integrating Time Accuracy into Existing Benchmarks We show how the proposed time accuracy metric can be beneficial when integrated into existing temporal alignment TSQA benchmarks (Dhingra et al., 2022; Margatina et al., 2023; Mousavi et al., 2024), enabling more fine-grained evaluation.

Table 5: Comparison of LLM performances across multiple-, unique-, and no-answer ("None") question types, evaluated on the Wikipedia dataset in the open-book setting. We report only **A** for the None type, as no time reference applies to no-answer cases.

	Multiple			Unique			None
Model	**A**	**T**	**AT**	**A**	**T**	**AT**	**A**
GPT-3.5	34.4	41.9	20.1	43.3	67.8	36.8	17.9
GPT-4	**60.3**	**77.8**	**49.8**	61.7	82.9	49.9	45.0
GPT-4o	58.1	67.3	42.2	67.8	68.7	43.7	**62.4**
Llama3.1-70B	48.6	45.7	29.4	**69.1**	51.8	33.2	44.2
Mixtral-8x7B	36.2	57.6	24.1	49.9	78.1	36.6	7.8
Gemma2-27B	49.7	56.1	29.1	61.9	63.6	41.7	20.0
Qwen2-72B	48.3	62.5	37.7	63.4	**86.4**	**57.0**	49.1
Granite3.1-8B	22.5	41.9	14.8	46.9	51.2	25.8	25.1

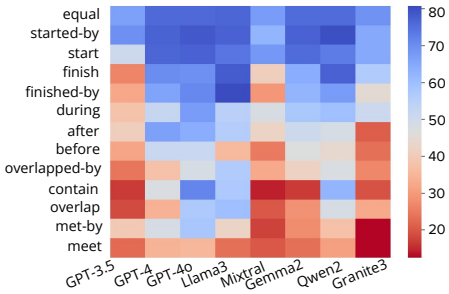


Figure 2: LLM performances on 13 temporal relations in the open-book setting.

These benchmarks use open-ended QA templates (e.g., "The president of Italy is __") and solely evaluate the final answer. To integrate **T** and assess model explanation as well, we simply modify the system prompt to elicit start date references from the model, without altering the original benchmark. In Sec. D.2, we provide a detailed case study with Dyknow (Mousavi et al., 2024), where we extend the benchmark with **T** and observe an F1-score of 0.96 for temporally aligned responses (i.e., both answer and time reference are correct), improving benchmark correctness against human verifications.

4.2 Breakdown of Temporal Reasoning Performance

We now evaluate the temporal reasoning ability of LLMs to understand diverse temporal conditions, analyzing performance by answer cardinality, temporal constraint type, and temporal span.

Performance by Answer Cardinality We evaluate LLM performances across different answer set sizes, expanding the traditional setup with a single answer. Depending on the generated temporal context, TDBench can yield multiple-answer or no-answer questions as well as single-answer questions. For example, a no-answer question might ask, *"Which president of the U.S. ended their term exactly half a year before January 20, 2001?"*, where no such president exists. Table 5 shows that models like GPT-4o perform robustly across question types, whereas models like Mixtral and GPT-3.5 show notable gaps, particularly underperforming on no-answer questions. For example, a model incorrectly answers "Bill Clinton" (term ended on January 20, 2001), likely due to matching the string "January 20, 2001" in the question rather than reasoning over "exactly half a year.", indicating that models may rely more on surface cues than true temporal reasoning.

Performance by Temporal Constraint Type We assess how well the LLMs handle different types of temporal constraints using the 13 distinct temporal relations. Fig. 2 shows that LLMs perform best on 'equal' relation-based constraints (e.g., "in 2025") – likely due to their prevalence in training data – while struggling with 'contain' and 'overlap', which require precise temporal reasoning over both start and end dates (e.g., started before January 1, 1985, and ended after December 30, 1992 for 'contain'). Interestingly, LLMs tend to comprehend start constraints (e.g., 'start', 'started-by') more accurately than end constraints (e.g., 'finish', 'finished-by'), which may stem from the autoregressive nature of LLMs that prioritizes earlier tokens in generation.

Performance by Temporal Span We evaluate LLM performance across different temporal spans under the closed-book setting, assessing how well LLMs utilize internal time-sensitive factual knowledge without external context. Fig. 3 shows the results for a single domain (*Countries*) (see Sec. D.3. for aggregated results across multiple domains) where we observe a gradual performance increase from 1985 to 2010, with a notable jump in the 1990–1995 interval. As this trend appears consistently across all models, we suggest it reflects shared characteristics of training data rather than model-specific behavior, where the 1990–1995 period may be better represented in the training data.

4.3 Evaluation of Multi-hop Questions

We assess LLM performance on multi-hop questions. As described in Sec. 3.3, these questions have implicit temporal contexts generated via temporal joins, and we construct 2-hop and 3-hop

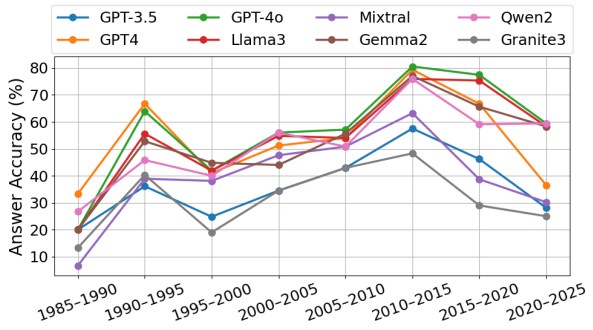


Figure 3: LLM performances across different time spans (1985-2025) in the closed-book setting. Additional results on multiple domains are presented in Sec. D.3.

Table 6: Performance comparison on multi-hop questions where $\mathbf{H_i}$ denotes the hallucination rate at the $(i+1)$-th hop given the correct i-th hop. Full results with 2-hop questions are in Table 27.

	3-hop			
Model	**A**	**AT**	**H_1**	**H_2**
GPT-3.5	33.8	33.8	**8.5**	7.6
GPT-4	57.1	52.5	10.8	0.5
GPT-4o	**90.4**	**87.9**	26.3	**0.0**
Llama3.1-70B	82.8	80.8	38.2	4.5
Mixtral-8x7B	60.1	49.0	19.5	10.6
Gemma2-27B	48.0	43.9	26.5	24.7
Qwen2-72B	68.2	59.1	35.1	5.6
Granite3.1-8B	11.1	11.1	10.3	77.8

questions by joining the *Olympic* and *Country* datasets. For the 2-hop setting, we use the TFD $game\_edition, role \xrightarrow{T} name$, where models should infer (1) the host country and time from a given Olympic name (e.g., 1988 Summer Olympics), and (2) the leader of the host country (e.g., president) at that time. For the 3-hop setting, we use $game\_round, role \xrightarrow{T} name$, where models should infer (1) the Olympic name from the round number (e.g., 24th Summer Olympics), (2) the host country and time, and (3) the leader at that time. An example QA is shown in Sec. B.3.

Performance by Reasoning Hops To effectively assess the reasoning process, we introduce $\mathbf{H}_i$, which measures the conditional probability of hallucination where a model answers the i-th hop correctly, but hallucinates on the $(i+1)$-st hop. Alongside the overall performances captured by **A** and **AT**, Table 6 shows the step-wise performances captured by $\mathbf{H}_i$, revealing the most challenging hop for each model. For example, GPT-4o and Llama3.1-70B hallucinate more at the first hop (i.e., higher $\mathbf{H}_1$), while Granite3.1-8B hallucinates more at the second hop (i.e., higher $\mathbf{H}_2$) in the 3-hop setting. These model-specific challenges highlight the value of TDBench's multi-hop generation capability, which enables a fine-grained diagnosis of intermediate reasoning failures.

Impact of Performance Improvement Techniques To mitigate reasoning errors in multi-hop settings, we evaluate the effectiveness of prompting strategies known to support model reasoning. Specifically, we compare RAG (Lewis et al., 2020), which augments prompts with retrieved Wikipedia passages; Chain-of-Thought (CoT) (Wei et al., 2022), which guides models to generate intermediate reasoning steps; and Time-CoT (Yin & Hu, 2024), a recent CoT variant designed for temporal reasoning – see CoT and Time-CoT prompts in Sec. D.4. As shown in Table 7, CoT and Time-CoT generally outperform RAG, which often retrieves relevant yet temporally misaligned contexts (see a case study in Sec. D.4). Between CoT and Time-CoT, no single method consistently outperforms the other, with effectiveness varying by model; see similar results with single-hop questions in Sec. D.4.

Table 7: Performance comparison on multi-hop questions when applying RAG, CoT, and Time-CoT. Best- and second-best performing methods for each model are highlighted in bold and underline, respectively.

Model	**Original**	**RAG**	**CoT**	**Time-CoT**
GPT-3.5	<u>63.1</u>	**71.2**	39.4	15.2
GPT-4	67.2	35.4	<u>92.4</u>	**93.9**
GPT-4o	79.3	89.9	<u>92.9</u>	**95.5**
Llama3.1-70B	83.8	73.2	**92.9**	<u>91.9</u>
Mixtral-8x7B	**72.7**	60.1	67.2	<u>71.2</u>
Gemma2-27B	77.8	40.9	**83.8**	<u>78.8</u>
Qwen2-72B	65.2	<u>78.8</u>	77.8	**85.4**
Granite3.1-8B	50.5	54.5	<u>70.2</u>	**72.2**

4.4 Correctness of TDBench

We evaluate the correctness of TDBench across three task types (Sec. 4.1 – Sec. 4.3). We compare TDBench's evaluation results with manual verification on 125 randomly sampled responses per task, using precision (P), recall (R), and F1-score (F1); see Sec. D.5 for metric definitions and details of manual verification. As shown in Table 8, TDBench achieves high agreement with manual verification, demonstrating the effectiveness of database-driven techniques for LLM benchmarking.

Table 8: Correctness of TDBench against manual verification. Fine-grained results are in Table 23.

Methods	**P**	**R**	**F1**
Temporal alignment	0.98	0.96	0.97
Temporal reasoning	0.87	0.91	0.88
Multi-hop	0.95	0.87	0.91

4.5 More Analyses

To further evaluate the applicability and robustness of TDBench, we conduct additional analyses: (1) *evaluation on synthetic medical data*, demonstrating how TDBench can be applied beyond real-world facts (Sec. D.6); (2) *evaluation of task-specific TSQA methods*, which underperform relative to the general-purpose models in the main experiments (Sec. D.7); and (3) *comparison with LLM-based TSQA methods*, which generate TSQA pairs by directly feeding raw data into LLMs, but can be more susceptible to hallucination and incur higher inference costs when processing the raw data (Sec. D.8).

5 Related Work

Factual Time-Sensitive Question-Answering TDBench differs from prior factual TSQA benchmarks in three main aspects: data source, QA construction, and evaluation methodology. Prior TSQA studies heavily centers on Wikidata (Jia et al., 2018; Chen et al., 2021; Dhingra et al., 2022; Margatina et al., 2023; Tan et al., 2023; Mousavi et al., 2024; Luo et al., 2025; Zhu et al., 2025; Islakoglu & Kalo, 2025) or Wikipedia (Jang et al., 2022; Kim et al., 2024; Wu et al., 2024; Xiong et al., 2024). While some recent work target tabular data (Gupta et al., 2023; Zhao et al., 2024), they remain limited to Wikipedia tables and often require additional Wikipedia page content for QA construction, restricting generalization beyond Wikipedia. In contrast, TDBench is not constrained by Wikidata/Wikipedia domains, enabling generalization to arbitrary temporal databases by building on database design principles such as TFDs. In terms of QA construction, existing benchmarks often rely on manually curated (Chen et al., 2021; Wei et al., 2023; Kasai et al., 2023; Gupta et al., 2023; Vu et al., 2023; Jia et al., 2024) or template-based QA (Table 9), which often covers limited temporal relations. In contrast, TDBench does not rely on manual construction or a fixed set of templates, while covering a richer set of temporal relations via temporal SQL. There are also LLM-based methods that generate TSQA pairs by processing raw databases via natural language prompting (Kim et al., 2024; Zhao et al., 2024), but TDBench enables more controlled and precise data processing by employing SQL-based data querying. Lastly, to our knowledge, we are the first to address the automatic evaluation of invalid model explanations in TSQA tasks.

Table 9: Comparison with TDBench against template-based factual TSQA benchmarks. We cover 13 temporal relations (Op #), without relying on the fixed set of templates (Temp #) while verifying both answers (**A**) and time references (**T**) during evaluation (Eval).

Method	Op #	Temp #	Eval
Dhingra et al. (2022)	1 (Equal)	9	**A**
Margatina et al. (2023)	1 (Equal)	16	**A**
Tan et al. (2023)	6	23	**A**
Mousavi et al. (2024)	1 (Equal)	27	**A**
TDBench (Ours)	13	(Unlimited)	**A**, **T**

Using SQL for QA Systems In QA systems, *Text-to-SQL* has been a primary research area (Qin et al., 2022; Hong et al., 2024), with the goal of (1) translating natural language questions into SQL queries and (2) retrieving answers from databases that serve as knowledge sources, thereby improving QA performance (Pasupat & Liang, 2015; Zhong et al., 2017; Yu et al., 2018; Rajkumar et al., 2022; Liu et al., 2022; Gao et al., 2023). In contrast, our methodology adopts an *SQL-to-Text* approach (Xu et al., 2018; Câmara et al., 2024; Zhang et al., 2024b), translating SQL queries into natural language questions. We perform this task for the purpose of generating QA pairs, rather than enhancing LLM performance through SQL-based retrieval. In particular, our distinction is to use temporal SQL – an extension of standard SQL with expressive temporal operators – to generate time-sensitive questions tailored to TSQA tasks, as well as other database techniques such as TFDs and temporal joins.

6 Conclusion

We proposed TDBench, which utilizes temporal databases and database techniques for systematic evaluation of factual TSQA. By leveraging database techniques, TDBench reduces the manual effort traditionally required in benchmark construction and maintenance, such as designing temporal contexts or updating QA pairs with new world knowledge. We also introduced a new metric called time accuracy for fine-grained TSQA evaluation, designing TDBench to automatically verify both the final answers and the time references by using SQL-based temporal constraints. Experiments revealed that a large portion of factually inconsistent responses with invalid time references can be overlooked in the answer-only evaluation setting, while uncovering model-specific weaknesses across constraint types, answer cardinality, and reasoning hops. We believe TDBench offers a new direction for TSQA evaluation by moving beyond Wikipedia/Wikidata and enabling domain-specific benchmarking.

Ethics statement

We believe our research addresses an important aspect of Trustworthy AI by evaluating the accuracy and reliability of LLMs under time-sensitive factual scenarios. In particular, we surface the issue of LLM hallucination in both final answers and time references, which can mislead users and undermine trust. By providing a systematic benchmarking framework to detect such cases, TDBench contributes toward building more reliable and transparent LLMs. As a dynamic framework, the choice of the database in TDBench inherently determines the benchmark content. We assume that it is the user's responsibility to ensure their chosen databases meet ethical standards and exclude harmful or private material. All datasets used in this study are publicly available and free of sensitive or harmful content.

Reproducibility statement

To ensure the reproducibility of our results, we provide the details of experimental setups in the supplementary material, including the proposed TDBench algorithm, system prompts, LLM hyperparameters (e.g., temperature), and details of datasets used in our study. In addition, we will release the GitHub repository for the TDBench framework, containing code and scripts for reproducing our results and documentation for extending the benchmark to new datasets.

The Use of Large Language Models

LLMs were mainly utilized as evaluation targets in this work. We also used LLMs to assist in the writing process (e.g., refining phrasing, enhancing clarity), but we did not employ LLMs for generating core research ideas or technical content.

References

James F Allen. Maintaining knowledge about temporal intervals. *Communications of the ACM*, 26 (11):832–843, 1983.

Jinze Bai, Shuai Bai, Yunfei Chu, Zeyu Cui, Kai Dang, Xiaodong Deng, Yang Fan, Wenbin Ge, Yu Han, Fei Huang, et al. Qwen technical report. *arXiv preprint arXiv:2309.16609*, 2023.

Vanessa Câmara, Rayol Mendonca-Neto, André Silva, and Luiz Cordovil. A large language model approach to sql-to-text generation. In *2024 IEEE International Conference on Consumer Electronics (ICCE)*, pp. 1–4. IEEE, 2024.

Wenhu Chen, Xinyi Wang, and William Yang Wang. A dataset for answering time-sensitive questions. *arXiv preprint arXiv:2108.06314*, 2021.

Bhuwan Dhingra, Jeremy R Cole, Julian Martin Eisenschlos, Daniel Gillick, Jacob Eisenstein, and William W Cohen. Time-aware language models as temporal knowledge bases. *Transactions of the Association for Computational Linguistics*, 10:257–273, 2022.

Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Amy Yang, Angela Fan, et al. The llama 3 herd of models. *arXiv preprint arXiv:2407.21783*, 2024.

Dawei Gao, Haibin Wang, Yaliang Li, Xiuyu Sun, Yichen Qian, Bolin Ding, and Jingren Zhou. Text-to-sql empowered by large language models: A benchmark evaluation. *arXiv preprint arXiv:2308.15363*, 2023.

IBM Granite Team. Granite 3.0 language models, October 2024. URL `https://github.com/ibm-granite/granite-3.0-language-models/`.

Daya Guo, Dejian Yang, Haowei Zhang, Junxiao Song, Ruoyu Zhang, Runxin Xu, Qihao Zhu, Shirong Ma, Peiyi Wang, Xiao Bi, et al. Deepseek-r1: Incentivizing reasoning capability in llms via reinforcement learning. *arXiv preprint arXiv:2501.12948*, 2025.

Vivek Gupta, Pranshu Kandoi, Mahek Bhavesh Vora, Shuo Zhang, Yujie He, Ridho Reinanda, and Vivek Srikumar. Temptabqa: Temporal question answering for semi-structured tables. *arXiv preprint arXiv:2311.08002*, 2023.

Zijin Hong, Zheng Yuan, Qinggang Zhang, Hao Chen, Junnan Dong, Feiran Huang, and Xiao Huang. Next-generation database interfaces: A survey of llm-based text-to-sql. *arXiv preprint arXiv:2406.08426*, 2024.

Yue Huang, Lichao Sun, Haoran Wang, Siyuan Wu, Qihui Zhang, Yuan Li, Chujie Gao, Yixin Huang, Wenhan Lyu, Yixuan Zhang, et al. Trustllm: Trustworthiness in large language models. *arXiv preprint arXiv:2401.05561*, 2024.

Duygu Sezen Islakoglu and Jan-Christoph Kalo. Chronosense: Exploring temporal understanding in large language models with time intervals of events. *arXiv preprint arXiv:2501.03040*, 2025.

Joel Jang, Seonghyeon Ye, Changho Lee, Sohee Yang, Joongbo Shin, Janghoon Han, Gyeonghun Kim, and Minjoon Seo. Temporalwiki: A lifelong benchmark for training and evaluating ever-evolving language models. *arXiv preprint arXiv:2204.14211*, 2022.

Christian S Jensen and Richard T Snodgrass. Temporal database., 2018.

Christian S Jensen, Richard T Snodgrass, and Michael D Soo. Extending existing dependency theory to temporal databases. *IEEE Transactions on Knowledge and Data Engineering*, 8(4):563–582, 1996.

Ziwei Ji, Nayeon Lee, Rita Frieske, Tiezheng Yu, Dan Su, Yan Xu, Etsuko Ishii, Ye Jin Bang, Andrea Madotto, and Pascale Fung. Survey of hallucination in natural language generation. *ACM computing surveys*, 55(12):1–38, 2023.

Zhen Jia, Abdalghani Abujabal, Rishiraj Saha Roy, Jannik Strötgen, and Gerhard Weikum. Tempquestions: A benchmark for temporal question answering. In *Companion Proceedings of the The Web Conference 2018*, pp. 1057–1062, 2018.

Zhen Jia, Philipp Christmann, and Gerhard Weikum. Tiq: A benchmark for temporal question answering with implicit time constraints. In *Companion Proceedings of the ACM Web Conference 2024*, pp. 1394–1399, 2024.

Albert Q Jiang, Alexandre Sablayrolles, Antoine Roux, Arthur Mensch, Blanche Savary, Chris Bamford, Devendra Singh Chaplot, Diego de las Casas, Emma Bou Hanna, Florian Bressand, et al. Mixtral of experts. *arXiv preprint arXiv:2401.04088*, 2024.

Junfeng Jiao, Saleh Afroogh, Yiming Xu, and Connor Phillips. Navigating llm ethics: Advancements, challenges, and future directions, 2024. URL https://arxiv.org/abs/2406.18841.

Jungo Kasai, Keisuke Sakaguchi, yoichi takahashi, Ronan Le Bras, Akari Asai, Xinyan Velocity Yu, Dragomir Radev, Noah A. Smith, Yejin Choi, and Kentaro Inui. Realtime QA: What's the answer right now? In *Thirty-seventh Conference on Neural Information Processing Systems Datasets and Benchmarks Track*, 2023. URL https://openreview.net/forum?id=HfKOIPCvsv.

Yujin Kim, Jaehong Yoon, Seonghyeon Ye, Sangmin Bae, Namgyu Ho, Sung Ju Hwang, and Se-Young Yun. Carpe diem: On the evaluation of world knowledge in lifelong language models. In Kevin Duh, Helena Gomez, and Steven Bethard (eds.), *Proceedings of the 2024 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies (Volume 1: Long Papers)*, pp. 5401–5415, Mexico City, Mexico, June 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.naacl-long.302. URL https://aclanthology.org/2024.naacl-long.302/.

Patrick Lewis, Ethan Perez, Aleksandra Piktus, Fabio Petroni, Vladimir Karpukhin, Naman Goyal, Heinrich Küttler, Mike Lewis, Wen-tau Yih, Tim Rocktäschel, et al. Retrieval-augmented generation for knowledge-intensive nlp tasks. *Advances in Neural Information Processing Systems*, 33: 9459–9474, 2020.

Stephanie Lin, Jacob Hilton, and Owain Evans. Truthfulqa: Measuring how models mimic human falsehoods. *arXiv preprint arXiv:2109.07958*, 2021.

Qian Liu, Bei Chen, Jiaqi Guo, Morteza Ziyadi, Zeqi Lin, Weizhu Chen, and Jian-Guang Lou. Tapex: Table pre-training via learning a neural sql executor. In *The Tenth International Conference on Learning Representations*, 2022.

Sigang Luo, Yinan Liu, Dongying Lin, Yingying Zhai, Bin Wang, Xiaochun Yang, and Junpeng Liu. Etrqa: A comprehensive benchmark for evaluating event temporal reasoning abilities of large language models. In *Findings of the Association for Computational Linguistics: ACL 2025*, pp. 23321–23339, 2025.

Alex Mallen, Akari Asai, Victor Zhong, Rajarshi Das, Daniel Khashabi, and Hannaneh Hajishirzi. When not to trust language models: Investigating effectiveness of parametric and non-parametric memories. In Anna Rogers, Jordan Boyd-Graber, and Naoaki Okazaki (eds.), *Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 9802–9822, Toronto, Canada, July 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.acl-long.546. URL https://aclanthology.org/2023.acl-long.546/.

Katerina Margatina, Shuai Wang, Yogarshi Vyas, Neha Anna John, Yassine Benajiba, and Miguel Ballesteros. Dynamic benchmarking of masked language models on temporal concept drift with multiple views. In Andreas Vlachos and Isabelle Augenstein (eds.), *Proceedings of the 17th Conference of the European Chapter of the Association for Computational Linguistics*, pp. 2881–2898, Dubrovnik, Croatia, May 2023. Association for Computational Linguistics. doi: 10.18653/v1/2023.eacl-main.211. URL https://aclanthology.org/2023.eacl-main.211/.

Seyed Mahed Mousavi, Simone Alghisi, and Giuseppe Riccardi. DyKnow: Dynamically verifying time-sensitive factual knowledge in LLMs. In Yaser Al-Onaizan, Mohit Bansal, and Yun-Nung Chen (eds.), *Findings of the Association for Computational Linguistics: EMNLP 2024*, pp. 8014–8029, Miami, Florida, USA, November 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.findings-emnlp.471. URL https://aclanthology.org/2024.findings-emnlp.471/.

Jio Oh, Soyeon Kim, Junseok Seo, Jindong Wang, Ruochen Xu, Xing Xie, and Steven Euijong Whang. Erbench: An entity-relationship based automatically verifiable hallucination benchmark for large language models. *arXiv preprint arXiv:2403.05266*, 2024.

OpenAI. Chatgpt. https://chat.openai.com, 2022.

OpenAI. Gpt-4 technical report, 2023.

OpenAI. Gpt-4o system card. *arXiv preprint arXiv:2410.21276*, 2024.

Panupong Pasupat and Percy Liang. Compositional semantic parsing on semi-structured tables. *arXiv preprint arXiv:1508.00305*, 2015.

Bowen Qin, Binyuan Hui, Lihan Wang, Min Yang, Jinyang Li, Binhua Li, Ruiying Geng, Rongyu Cao, Jian Sun, Luo Si, et al. A survey on text-to-sql parsing: Concepts, methods, and future directions. *arXiv preprint arXiv:2208.13629*, 2022.

Nitarshan Rajkumar, Raymond Li, and Dzmitry Bahdanau. Evaluating the text-to-sql capabilities of large language models. *arXiv preprint arXiv:2204.00498*, 2022.

Kai Sun, Yifan Ethan Xu, Hanwen Zha, Yue Liu, and Xin Luna Dong. Head-to-tail: how knowledgeable are large language models (llms)? aka will llms replace knowledge graphs? *arXiv preprint arXiv:2308.10168*, 2023.

Qingyu Tan, Hwee Tou Ng, and Lidong Bing. Towards benchmarking and improving the temporal reasoning capability of large language models. *arXiv preprint arXiv:2306.08952*, 2023.

Gemma Team, Morgane Riviere, Shreya Pathak, Pier Giuseppe Sessa, Cassidy Hardin, Surya Bhupatiraju, Léonard Hussenot, Thomas Mesnard, Bobak Shahriari, Alexandre Ramé, et al. Gemma 2: Improving open language models at a practical size. *arXiv preprint arXiv:2408.00118*, 2024.

Md Nayem Uddin, Amir Saeidi, Divij Handa, Agastya Seth, Tran Cao Son, Eduardo Blanco, Steven R Corman, and Chitta Baral. Unseentimeqa: Time-sensitive question-answering beyond llms' memorization. *arXiv preprint arXiv:2407.03525*, 2024.

Tu Vu, Mohit Iyyer, Xuezhi Wang, Noah Constant, Jerry Wei, Jason Wei, Chris Tar, Yun-Hsuan Sung, Denny Zhou, Quoc Le, et al. Freshllms: Refreshing large language models with search engine augmentation. *arXiv preprint arXiv:2310.03214*, 2023.

Cunxiang Wang, Xiaoze Liu, Yuanhao Yue, Xiangru Tang, Tianhang Zhang, Cheng Jiayang, Yunzhi Yao, Wenyang Gao, Xuming Hu, Zehan Qi, et al. Survey on factuality in large language models: Knowledge, retrieval and domain-specificity. *arXiv preprint arXiv:2310.07521*, 2023.

Jason Wei, Xuezhi Wang, Dale Schuurmans, Maarten Bosma, Fei Xia, Ed Chi, Quoc V Le, Denny Zhou, et al. Chain-of-thought prompting elicits reasoning in large language models. *Advances in neural information processing systems*, 35:24824–24837, 2022.

Yifan Wei, Yisong Su, Huanhuan Ma, Xiaoyan Yu, Fangyu Lei, Yuanzhe Zhang, Jun Zhao, and Kang Liu. Menatqa: A new dataset for testing the temporal comprehension and reasoning abilities of large language models. *arXiv preprint arXiv:2310.05157*, 2023.

Xiaobao Wu, Liangming Pan, Yuxi Xie, Ruiwen Zhou, Shuai Zhao, Yubo Ma, Mingzhe Du, Rui Mao, Anh Tuan Luu, and William Yang Wang. Antileak-bench: Preventing data contamination by automatically constructing benchmarks with updated real-world knowledge. *arXiv preprint arXiv:2412.13670*, 2024.

Siheng Xiong, Ali Payani, Ramana Kompella, and Faramarz Fekri. Large language models can learn temporal reasoning. In Lun-Wei Ku, Andre Martins, and Vivek Srikumar (eds.), *Proceedings of the 62nd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 10452–10470, Bangkok, Thailand, August 2024. Association for Computational Linguistics. doi: 10.18653/v1/2024.acl-long.563. URL https://aclanthology.org/2024.acl-long.563/.

Kun Xu, Lingfei Wu, Zhiguo Wang, Yansong Feng, and Vadim Sheinin. Sql-to-text generation with graph-to-sequence model. *arXiv preprint arXiv:1809.05255*, 2018.

Reda Yacouby and Dustin Axman. Probabilistic extension of precision, recall, and f1 score for more thorough evaluation of classification models. In *Proceedings of the first workshop on evaluation and comparison of NLP systems*, pp. 79–91, 2020.

Baosheng Yin and Naiyu Hu. Time-cot for enhancing time reasoning factual question answering in large language models. In *2024 International Joint Conference on Neural Networks (IJCNN)*, pp. 1–8. IEEE, 2024.

Tao Yu, Rui Zhang, Kai Yang, Michihiro Yasunaga, Dongxu Wang, Zifan Li, James Ma, Irene Li, Qingning Yao, Shanelle Roman, et al. Spider: A large-scale human-labeled dataset for complex and cross-domain semantic parsing and text-to-sql task. *arXiv preprint arXiv:1809.08887*, 2018.

Chenhan Yuan, Qianqian Xie, Jimin Huang, and Sophia Ananiadou. Back to the future: Towards explainable temporal reasoning with large language models. In *Proceedings of the ACM on Web Conference 2024*, pp. 1963–1974, 2024.

Bin Zhang, Yuxiao Ye, Guoqing Du, Xiaoru Hu, Zhishuai Li, Sun Yang, Chi Harold Liu, Rui Zhao, Ziyue Li, and Hangyu Mao. Benchmarking the text-to-sql capability of large language models: A comprehensive evaluation. *arXiv preprint arXiv:2403.02951*, 2024a.

Bin Zhang, Yuxiao Ye, Guoqing Du, Xiaoru Hu, Zhishuai Li, Sun Yang, Chi Harold Liu, Rui Zhao, Ziyue Li, and Hangyu Mao. Benchmarking the text-to-sql capability of large language models: A comprehensive evaluation, 2024b. URL https://arxiv.org/abs/2403.02951.

Bowen Zhao, Zander Brumbaugh, Yizhong Wang, Hannaneh Hajishirzi, and Noah A Smith. Set the clock: Temporal alignment of pretrained language models. *arXiv preprint arXiv:2402.16797*, 2024.

Victor Zhong, Caiming Xiong, and Richard Socher. Seq2sql: Generating structured queries from natural language using reinforcement learning, 2017. URL https://arxiv.org/abs/1709.00103.

Zhiyuan Zhu, Yusheng Liao, Zhe Chen, Yuhao Wang, Yunfeng Guan, Yanfeng Wang, and Yu Wang. Evolvebench: A comprehensive benchmark for assessing temporal awareness in llms on evolving knowledge. In *Proceedings of the 63rd Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, pp. 16173–16188, 2025.

A Appendix – Formal Definitions of FDs and TFDs

Continuing from Sec. 2, we introduce formal definitions on *temporal functional dependencies* (TFDs) and *temporal joins*. Let R and S be temporal relation schemas where two timestamps T_s and T_e denote the start and end timestamps of each relation, respectively.

$$R = (A_1, \ldots, A_n, C_1, \ldots, C_k, T_s, T_e)$$
$$S = (B_1, \ldots, B_m, C_1, \ldots, C_k, T_s, T_e)$$

For an effective illustration, let $\{A_i\}_{i=1}^n$ and $\{B_i\}_{i=1}^m$ denote the unique attributes of schemas R and S, respectively, and let $\{C_i\}_{i=1}^k$ represent the attributes shared by both.

We first introduce the definition of temporal FDs (Jensen et al., 1996) below.

Definition A.1 (Temporal functional dependencies)**.** *Let X and Y be sets of non-timestamp attributes of a temporal relation schema R, and let t_1 and t_2 be arbitrary times, with t_1 not exceeding the current time. A temporal functional dependency, denoted as $X \xrightarrow{T} Y$, exists on R if, for all meaningful instances r of R – that is, database states that are valid, consistent, and free of contradictions – the following holds:*

$$\forall t_1, t_2,\ \forall u_1, u_2 \in \tau_{t_2}(\rho_{t_1}(r)),\ u_1[X] = u_2[X] \implies u_1[Y] = u_2[Y],$$

where $\rho_{t_1}(r)$ selects tuples valid at t_1, and $\tau_{t_2}(\cdot)$ further restricts the result to tuples visible at t_2.

The above definition formally states that for any valid time intervals $[t_1, t_2]$, if two tuples u_1 and u_2 share the same values for X, these tuples must also share the same values for Y.

We now introduce the definition of temporal natural join (Jensen & Snodgrass, 2018) below.

Definition A.2 (Temporal natural join)**.** *Let r and s be instances of R and S, respectively. The temporal natural join of r and s, denoted as $r \bowtie^T s$, is defined as:*

$$r \bowtie^T s = \{z \mid \exists u \in r, \exists v \in s\,(u[C_1, ..., C_k] = v[C_1, ..., C_k] \wedge$$
$$z[A_1, ..., A_n] = u[A_1, ..., A_n] \wedge z[B_1, ..., B_m] = v[B_1, ..., B_m] \wedge z[C_1, ..., C_k] = v[C_1, ..., C_k] \wedge$$
$$z[T_s, T_e] = \texttt{overlap}(u[T_s, T_e], v[T_s, T_e]) \wedge z[T_s, T_e] \neq \emptyset)\},$$

where z represents the result tuple, and $\texttt{overlap}(u[T_s, T_e], v[T_s, T_e])$ computes the intersection of the valid time intervals from u and v.

The first two lines ensure that tuples u and v match on the shared attributes $\{C_i\}_{i=1}^k$ and concatenate the unique attributes $\{A_i\}_{i=1}^n$ and $\{B_i\}_{i=1}^m$, along with a single copy of $\{C_i\}_{i=1}^k$. The third line ensures that the join operation is performed only on tuples with overlapping valid time intervals.

B Appendix – More Details on TDBench Framework

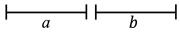
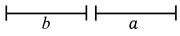
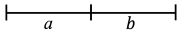
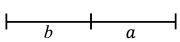
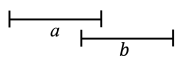
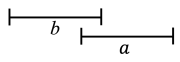
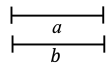
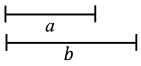
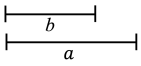
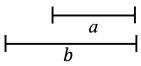
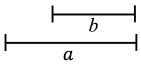
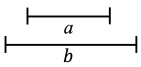
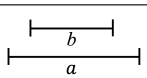
Continuing from Sec. 3, we provide more details on the TDBench framework.

B.1 Generated SQL Conditions and Time Accuracy Criteria

Continuing from Sec. 3 and Sec. 4, we provide more details on SQL conditions generated in TDBench. We design these conditions based on the interval relations from the database literature (Allen, 1983) and define the corresponding time accuracy criteria, as shown in Table 10.

SQL Conditions to Generate Up-to-date Questions For Temporal Alignment Task The temporal alignment task requires grounding questions in a specific temporal condition – "current" – to evaluate whether LLMs provide up-to-date knowledge. The "current" condition can be generated in various ways depending on the data format (e.g., by setting the end date to a maximum possible date like 99-99-99 or to NULL). We adopt the NULL format, which can produce more readable predicates (e.g., end IS NULL) than the maximum date format (e.g., start < CURRENT_DATE and CURRENT_DATE < end) and thus can facilitate the following SQL-to-text conversion step (Sec. 3.1). Given the NULL format, we treat the "current" condition as a special case of the "overlap" relation, where the event begins before the present and has no defined end, as shown in Table 10.

Table 10: Illustration of the 13 temporal relation (Allen, 1983) between temporal intervals a and b, from which we generate the SQL condition, temporal context, and the corresponding time accuracy criteria. Diverse temporal contexts can be constructed by sampling different values for a and b. In these examples, a denotes a president's term, and *September 20, 2000* and *March 20, 2001* correspond to b.start and b.end, respectively. For the "overlap" relation, we design two conditions: one for the general overlap between time intervals, and another specifically for handling current data (e.g., current president) where the end timestamp can be unspecified (e.g., `NULL`) – see Sec. B.1 for more details on handling current data. We show examples of the generated natural language questions from these SQL conditions in Sec. B.3.

Relation	Interval Diagram	SQL Condition	Example Temporal Context	Criteria
a before b		a.end < b.start	A president who ends before *September 20, 2000*	end
a after b		a.start > b.end	A president who starts after *March 20, 2001*	start
a meet b		a.end = b.end - b.length	A president who ends exactly *half a year* before *March 20, 2001*	end
a met-by b		a.start = b.start + b.length	A president who starts exactly *half a year* after *September 20, 2000*	start
a overlap b		a.start < b.start ∧ b.start < a.end < b.end	A president who starts before *September 20, 2000* and ends between *September 20, 2000* and *March 20, 2001*	start, end
		a.start < b.start ∧ a.end IS NULL	A president who is currently serving	start
a overlapped-by b		a.end > b.end ∧ b.start < a.start < b.end	A president who starts between *September 20, 2000* and *March 20, 2001* and ends after *March 20, 2001*	start, end
a equal b		a.start = b.start ∧ a.end = b.end	A president who starts in *September, 2000* and ends in *March, 2001*	start, end
a start b		a.start = b.start ∧ a.end < b.end	A president who starts in *September, 2000* and ends before *March, 2001*	start, end
a started-by b		a.start = b.start ∧ a.end > b.end	A president who starts in *September, 2000*	start
a finish b		a.start > b.start ∧ a.end = b.end	A president who starts after *September 20, 2000* and ends in *March, 2001*	start, end
a finished-by b		a.start < b.start ∧ a.end < b.end	A president who ends in *March, 2001*	end
a during b		a.start > b.start ∧ a.end < b.end	A president who starts after *September 20, 2000* and ends before *March 20, 2001*	start, end
a contain b		a.start < b.start ∧ a.end > b.end	A president who starts before *September 20, 2000* and ends after *March 20, 2001*	start, end

B.2 Pseudocode of Genqueries

Continuing from Sec. 3.1 and Sec. 3.2, we provide the pseudocode of `Genqueries` (Alg. 1), which systematically generates temporal SQL queries from an input temporal database.

Algorithm Procedure of `Genqueries` We explain the `Genqueries` algorithm (Alg. 1) line by line. `Genqueries` begins by initializing an empty list of queries (Line 1). For each tuple in

Algorithm 1 The proposed `Genqueries` algorithm

Input: Temporal database relation s with schema S, list of temporal functional dependencies (TFDs; Sec. 2) $\mathcal{F} = \{X_1 \xrightarrow{T} Y_1, \ldots, X_n \xrightarrow{T} Y_n\}$ where X_i and Y_i denote sets of attributes in the schema S for $i \in n$, list of temporal relations $\mathcal{R} = \{\text{before}, \text{after}, \ldots, \text{contain}\}$ shown in Table 10
Output: List of generated temporal SQL queries $\mathcal{G}$

1: $\mathcal{G} \leftarrow \emptyset$
2: **for** each tuple $u \in r$ **do**
3: **for** each TFD $f : X_i \xrightarrow{T} Y_i \in \mathcal{F}$ **do**
4: *# Phase 1: Generate base query using a TFD*
5: $q_b \leftarrow$ SELECT Y_i FROM s WHERE $X_i = u.X_i$
6: *# Phase 2: Add temporal constraints*
7: **for** each operation $r \in \mathcal{R}$ **do**
8: Sample a random time interval $b = (t_s, t_e)$
9: $q_t \leftarrow q_b + r(u, b)$ according to Table 10
10: $\mathcal{G} \leftarrow \mathcal{G} \cup \{q_t\}$
11: **end for**
12: **end for**
13: **end for**
14: **return** $\mathcal{G}$

the database and each TFD defined in the database (Lines 2–3), we construct a base SQL query by selecting the Y_i attributes conditioned on the X_i attributes of the tuple (Line 4). We then add temporal conditions to this base query (Line 5) by iterating over a set of predefined temporal operations, such as "before", "after", or "overlap" (Line 6), using the relation-SQL condition mapping in Table 10. For each operation, we sample a random time interval (Line 7), adding the temporal constraint to the base query (Line 8), and append the resulting query to the output list (Line 9). After processing all tuples and TFDs, `Genqueries` returns the complete set of generated temporal SQL queries (Line 10).

Extending `Genqueries` We can further extend `Genqueries` to incorporate more diverse TSQA evaluation scenarios. While `Genqueries` primarily utilizes TFD-selected attributes to automatically construct QA pairs (i.e., using X as the question and Y as the answer for a given TFD $X \xrightarrow{T} Y$), `Genqueries` also supports user-defined extensions where users can manually specify alternative sets of question and answer attributes. For example, given the relation *Leader(country, role, name, gender, start, end)* (Table 1) and the TFD $country, role \xrightarrow{T} name$, one can extend the answer to include both $name$ and $gender$, while still using $country, role$ as the question. Although this extension requires manual input to specify attribute sets, `Genqueries` still greatly simplifies the QA construction process compared to manual construction or template creation. In addition, SQL's expressiveness allows flexible extensions to richer question types. For example, aggregation operators (e.g., `GROUP BY`, `HAVING`) enable event-counting questions like "Which president has been elected for the third time?", which can be generated from the condition "`GROUP BY... HAVING COUNT(*)=3`" and require the model to count specific events throughout history.

B.3 More details on Natural Language QA Conversion

Continuing from Sec. 3.1, we provide more details on the natural language conversion step, where we use GPT-4o (OpenAI, 2024) as an SQL-to-text translator.

System Prompt for SQL-to-text The following prompt is an example system prompt used in our zero-shot setting for SQL-to-text conversion. We set the temperature parameter of GPT-4o to 0.3 to promote diverse paraphrasing. The prompt instructs the model to convert SQL queries into natural language questions based on the given schema and generate three different phrasings per query, where more than three questions can be generated if desired by modifying the prompt accordingly.

```
The following SQL query is about a relational database Leader(country,
role, name, start, end), where start and end represent date information.
Convert the provided SQL query into a natural language question.
```

```
Generate three different questions, each starting with Q:.
Only return the generated questions.
```

Accuracy of SQL-to-text We assess the accuracy of SQL-to-text conversion in the above setup by randomly sampling 130 generated questions during the conversion and manually verifying whether the questions correspond to the underlying query. We observe 91.5% accuracy, consistent with recent findings that modern LLMs have strong zero-shot performance on SQL-to-text tasks (Zhang et al., 2024a). We analyze error cases as follows:

- *Prime ministers of Japan → Japanese prime minister*: Although a prime minister of a country may not necessarily be a citizen, the model often assumes nationality based on the position, making this the most common error type.
- *November 1st → November*: In some cases, specific dates (e.g., November 1st) are generalized to the corresponding month (e.g., November), introducing potential ambiguity.
- *Calculation error*: When processing temporal operations like DATE('2006-07-17 00:00:00', '-2 months') in the query, the model occasionally makes date calculation errors. However, such errors are relatively rare, occurring in fewer than 1% of cases.

Examples of Generated QA pairs In addition to the example QA pairs shown in the main text (Table 3) generated from the "meet" relation, we present additional examples across temporal relations. Table 11 and Table 12 show QA pairs derived from the "contains" and "overlap" relations, respectively, which are two examples of temporal relations rarely covered in prior TSQA benchmarks. Table 13 shows QA pairs from an additional SQL condition for the "overlap" relation, specifically designed to target current data (see Sec. B.1 for more details). Table 14 shows multi-hop QA pairs generated by using temporal joins (Sec. A).

Table 11: A single SQL query (e.g., for the "contain" relation) generates multiple QA pairs by translating into diverse natural language questions with the same answer. To evaluate both answer and time accuracy, the SQL query also outputs a relation-specific time reference (e.g., `start` and `end` for the "contain" relation), defined in Table 10.

SQL Query (relation="contain")	**Generated QA**
`SELECT name, start, end FROM Leader WHERE Country='Japan' AND Role='Emperor' AND Start < '2019-10-01' AND End > '2024-08-26'`	**[Questions]** "Who was the Emperor of Japan whose term started before October 1, 2019, and ended after August 26, 2024?", "What is the name of the Emperor of Japan who began their role before October 1, 2019, and ended it after August 26, 2024?"... **[Answer]** Akihito **[Time reference]** 1989-01-07 (start), 2019-05-01 (end)
[Model Response (Gemma2-27B)] *Akihito*. He reigned from *1989-01-07* to *2019-05-01*.	

B.4 Formal Definition of Time Accuracy

Continuing from Sec. 3.2, we present the formal definition of the proposed time accuracy metric.

We begin by defining the *set of time references* $\mathcal{T}$, which captures the time references to be verified in LLM responses. Since we primarily generate questions asking about real world events – each grounded with a start date and end date – we set $\mathcal{T} = \{t_s, t_e\}$, where t_s and t_e denote the start and end dates, respectively.

We then define the *question-reference function* $f : q \rightarrow \mathcal{T}$, which maps a question to the time references to be verified. This function can be flexibly designed based on the temporal contexts expressed in the question. In our setup, the underlying SQL queries explicitly specify which time reference are relevant to answer selection process (e.g., an SQL condition such as "start < January 2001" implies reliance on t_s). Accordingly, we define f with respect to the temporal relation used in the SQL query, as summarized in Table 10.

Table 12: A single SQL query (e.g., for the "overlap" relation) generates multiple QA pairs by translating into diverse natural language questions with the same answer. To evaluate both answer and time accuracy, the SQL query also outputs a relation-specific time reference (e.g., `start` and `end` for the "overlap" relation), defined in Table 10.

SQL Query (relation="overlap")	**Generated QA**
`SELECT name, start, end FROM Leader WHERE Country='Germany' AND Role='President' AND Start < '2003-09-30' AND End BETWEEN '2003-09-30' and '2007-06-30'`	**[Questions]** "Who was the president of Germany who started their term before September 30, 2003, and ended their term between September 30, 2003, and June 30, 2007?", "Can you list the names of the presidents of Germany whose terms began before September 30, 2003, and ended between September 30, 2003, and June 30, 2007?"... **[Answer]** Johannes Rau **[Time reference]** 1999-07-01 (start), 2004-06-30 (end)
[Model Response (Qwen2-72B)] *Johannes Rau*, who started his term on *July 1, 1999*, and ended it on *June 30, 2004*.	

Table 13: A single SQL query (e.g., for the "overlap" relation to target current data) generates multiple QA pairs by translating into diverse natural language questions with the same answer. To evaluate both answer and time accuracy, the SQL query also outputs a relation-specific time reference (e.g., `start`), defined in Table 10.

SQL Query (relation="overlap")	**Generated QA**
`SELECT name, start FROM Leader WHERE Country='Netherlands' AND Role='King' AND End IS NULL`	**[Questions]** "Who is currently serving as the King of the Netherlands?", "What is the name of the individual who is the reigning King in the Netherlands?"... **[Answer]** Willem-Alexander **[Time reference]** 2013-04-30 (start)
[Model Response (Llama3.1-70B)] King *Willem-Alexander*, since *April 2013*.	

Table 14: A single SQL query (e.g., for a joined relation) generates multiple QA pairs by translating into diverse natural language questions with the same answer. To evaluate both answer and time accuracy, the SQL query also outputs timestamp attributes (e.g., `start`, `end`). $\bowtie^T$ denote the temporal join operator, which only joins tuples with overlapping valid time intervals – see formal definition of temporal join in Sec. A.

SQL Query (temporal join)	**Generated QA**
`SELECT name, start, end FROM Leader` $\bowtie^T$ `Olympic WHERE game_edition='7th Winter' AND Role='President'`	**[Questions]** "Who was the president of the host country for the 7th Winter Olympic Games?", "Can you provide the name of the president of the host country during the 7th edition of the Winter Olympics?"... **[Answer]** Giovanni Gronchi **[Time reference]** 1955-05-11 (start), 1962-05-11 (end)
[Model Response (GPT-4o)] The 7th Winter Olympic Games were held in Cortina d'Ampezzo, Italy in February 1956. The President of Italy at that time was *Giovanni Gronchi*, who served from *May 1955* to *May 1962*.	

We finally define the time accuracy $\mathbf{T}$ given a question q as follows:

$$\mathbf{T}(q) = \frac{|\{t \in f(q) | t \in \text{model response}\}|}{|f(q)|} \times 100(\%). \quad (1)$$

Note that for temporal relation types requiring multiple time references (e.g., "contain" in Table 11), partial credit is given when only a subset is correctly included in the model response.

B.5 TIME ACCURACY EVALUATION WITH LLM-JUDGE

Continuing from Sec. 3.2, we provide more details on time accuracy evaluation, where we use Deepseek-R1-14B (Guo et al., 2025) as an LLM-judge.

System Prompt for LLM-Judge The following system prompt shows the instruction for time accuracy evaluation, consistent with the formal definition in Eq. 1. As shown in the prompt, we opt to use LLM-Judge to capture various expressions of time references (e.g., "26 Jan 2025", "2025/01/26"), which may be missed by exact-match methods that directly compares gold time reference strings ({entity_date}) against the evaluated model response ({response}).

```
You are given a reference **start date** and **end date**.
Check whether the response correctly includes both dates, even if they
are expressed in a different but equivalent format (e.g., '26 Jan 2025',
'January 26, 2025', '2025/01/26', etc.).

- If **both** of the two dates is are correctly mentioned with the
intended meaning (i.e., the start date is described as the start date,
and the end date as the end date), respond with **"Yes"**.
- If **one** of the two dates is correctly mentioned with the intended
meaning, respond with **"Half"**.
- If **neither** date is correctly mentioned with the correct meaning,
respond with **"No"**.
Your answer must be one of: 'Yes', 'Half', or 'No'. Be concise.

{entity_date}

**Response:**
{response}

**Answer:
```

Accuracy of LLM-Judge in Time Accuracy Evaluation Similarly to the manual verification setup in Sec. B.3, we assess the effectiveness of LLM-Judge in time accuracy evaluation by randomly sampling 130 responses and manually verifying whether the evaluation aligns with the instruction above. We observe 91.1% accuracy, with most errors arising from instruction misinterpretation (e.g., assessing end dates when only assessing start dates is required) and date match failures (e.g., failing to match the gold time reference of "1993-04-28" and "April 1993" in the model response).

We note that using stronger LLMs can further enhance evaluation correctness; for instance, we observe that using GPT-4o under the same setup yields higher accuracy (95.5%). However, we opt not to use GPT-4o in our main experiments, as it is one of the evaluated models and may incur potential bias during evaluation if used as a judge.

B.6 ADDITIONAL CONTEXT CONSTRUCTION

Continuing from Sec. 3.2, we provide more details on context construction used in the open-book setting. As illustrated in Fig. 4, we append both relevant rows and irrelevant rows from the table with the gold answer to effectively evaluate LLMs' temporal reasoning abilities given a time-sensitive question. Relevant rows are retrieved by (1) removing the temporal condition from the underlying SQL query of the question and (2) executing the modified query on the database, returning entities across different periods (e.g., all U.S. presidents when the question asks about the U.S. president in 2019). We randomly sample the irrelevant rows in the table.

C APPENDIX – MORE DETAILS ON EXPERIMENTAL SETUPS

Continuing from Sec. 4, we provide more details on experimental settings, system prompts, and datasets.

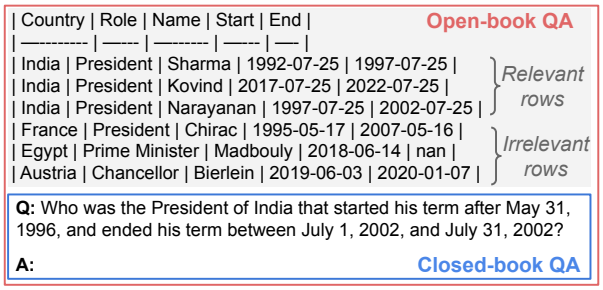


Figure 4: Open-book vs. Closed-book QA in TDBench. The open-book setting provides table rows as additional context, while the closed-book setting poses only the question.

C.1 Experimental Setups and System Prompts

Experiment Settings We use the following LLM versions: GPT-3.5 (2024-05-01-preview), GPT-4 (2025-01-01-preview), GPT-4o (2024-02-01), Llama3.1-70B (2024-07-23), Mixtral-8x7B (2023-12-11), Gemma2-27B (2024-06-27), Qwen2-72B (2023-08-03), and Granite3.1-8B (2024-12-18). All experiments are conducted on NVIDIA Quadro RTX 8000 GPUs.

System Prompts for TSQA Tasks We use the following system prompts for the TSQA tasks: the upper prompt is used for the temporal alignment task (Sec. 4.1), and the lower prompt is used for the temporal reasoning task (Sec. 4.2). As the prompts explicitly require time information in the rationale, responses that omit such references are marked incorrect in the time accuracy evaluation. This policy is applied uniformly across all models to ensure consistent and fair TSQA benchmarking, reflecting our goal of evaluating both final answers and explanations.

```
Answer the following question. Provide the short direct answer that
includes both the factual answer and the date information (month and
year) of the fact, prefixed with the word 'since'. Say 'unsure' if you
don't know. Be concise.
```

```
Answer the following question. Provide the short direct answer that
includes both the factual answer and rationale with the date information
of the fact. If there is no valid answer, respond with 'No answer'.
If there is one correct answer, return it as a short sentence.
If there are multiple valid answers, present them clearly as bullet
points. If you are unsure, respond with 'unsure'. Be concise.
```

C.2 More Details on Datasets

Continuing from Sec. 4, we provide more details on the temporal databases used in our experiments. Table 15 summarizes the schema, selected TFDs, and the number of questions generated from each dataset. Table 16 presents example questions generated by converting TFDs. Using these datasets, we construct 2,079 temporal alignment, 6,756 temporal reasoning, and 396 multi-hop questions, with additional questions readily generable if needed.

Wikipedia We select domains following the conventional TSQA benchmarking literature (Dhingra et al., 2022; Margatina et al., 2023; Tan et al., 2023; Mousavi et al., 2024), including *Country*, *Athlete*, *Organization*, and *Olympic* datasets. We also follow the entity selection step of Mousavi et al. (2024), which select entities likely to appear in most LLM training corpora to reduce performance variance caused by entity frequency when retrieving facts (Mallen et al., 2023; Sun et al., 2023). All datasets were retrieved on 02 January 2025.

Domain-specific To demonstrate the applicability of TDBench beyond Wikipedia-based datasets, we model domain-specific TSQA scenarios across four contexts: *Legal*, *Environmental*, *Cultural*, and *Social*. These domains are represented by datasets on same-sex marriage laws sourced from

Table 15: Details of the temporal databases used in our experiments.

Data Source	Question #	Schema	TFD
Wikipedia	6,177	*Country(country, role, name, start, end)*	*country, role* $\xrightarrow{T}$ *name*
		Athlete(name, team, sport, start, end)	*name, sport* $\xrightarrow{T}$ *team*
		Organization(org_name, type, role, name, start, end)	*org_name, type, role* $\xrightarrow{T}$ *name*
		Olympic(game_round, game_edition, city country, season, game_name, start, end)	*game_round, role* $\xrightarrow{T}$ *name (joined)* *game_edition, role* $\xrightarrow{T}$ *name (joined)*
Domain-specific	1,704	*Law(country, law_type, legality, start, end)*	*country, law_type* $\xrightarrow{T}$ *legality*
		Carbon Tax(jurisdiction, tax_type, instrument_name, status, start, end)	*jurisdiction, type* $\xrightarrow{T}$ *status*
		Heritage(heritage_element, member_state, status, region, start, end)	*heritage_element* $\xrightarrow{T}$ *status*
		Netflix(title, director, cast, release_year, popularity, start, end)	*title* $\xrightarrow{T}$ *director*
Synthetic	1,350	*Medical(name, gender, blood_type medication, doctor, hospital, insurance_provider, billing_amount)*	*name, gender, blood_type* $\xrightarrow{T}$ *doctor* *name, gender, blood_type* $\xrightarrow{T}$ *medication*

Table 16: Examples of base questions generated from TFDs across datasets. The proposed `Genqueries` algorithm (Alg. 1) converts the TFDs listed in Table 15 into these base questions and augments them with diverse temporal constraints.

Data Source	Example Questions Generated From TFDs
Wikipedia	• *Country*: Who is serving as the president of Italy? • *Athlete*: What team did Stephen Curry play for in basketball? • *Organization*: Which person began their tenure as general secretary at the United Nations organization? • *Olympic*: Can you provide the name of the president of the host country during the 7th edition of the Winter Olympics?
Domain-specific	• *Law*: Is joint adoption by same-sex couples legal or illegal in Argentina? • *Carbon Tax*: Is the carbon tax mechanism in Finland active? • *Heritage*: Is the heritage element "Cheoyongmu" inscribed or proclaimed? • *Netflix*: Who directed the most recent release of the movie titled "Attack on Titan"?
Synthetic	• Who was the doctor for Jerry Martin, a male patient with blood type A+? • Which medication is given to Kenneth Jacobs, a female patient with AB+ blood type?

the ILGA World databases[2], a global knowledge base on legal frameworks and human right bodies, retrieved on 02 January 2025; carbon taxation data sourced from the World Bank Group's "State and Trends of Carbon Pricing Dashboard"[3], retrieved on 17 October 2024; UNESCO heritage elements sourced from the official UNESCO website[4], retrieved on 17 October 2024; and Netflix TV shows data sourced from Kaggle[5], retrieved on 05 May 2025. For the Netflix dataset, we only consider TV series that share the same title, but have been remade over time with different directors.

Synthetic We also show how TDBench can be applied to synthetic datasets by using the *Medical* dataset, which contains synthetic patient records sourced from Kaggle[6], retrieved on 05 May 2025.

[2]https://database.ilga.org/en

[3]https://carbonpricingdashboard.worldbank.org/compliance/instrument-detail

[4]https://whc.unesco.org/en/list/

[5]https://www.kaggle.com/code/sonawanelalitsunil/netflix-movies-tv-shows-till-2025

[6]https://www.kaggle.com/datasets/prasad22/healthcare-dataset

D APPENDIX – MORE EXPERIMENTAL RESULTS

Continuing from Sec. 4, we provide more details on experimental results.

D.1 ERROR ANALYSIS ON TEMPORAL ALIGNMENT EVALUATION

Continuing from Sec. 4.1, we present example error cases in the temporal alignment task, where LLMs often hallucinate time references while providing correct answers. Table 17 and Table 18 show such responses from the Heritage and Netflix datasets, respectively, where LLMs generate inaccurate time references (e.g., "December 2011" and "January 2020") alongside correct answers (e.g., "Inscribed" and "Mehmet Ada Öztekin"). These cases indicates that LLMs struggle to accurately align the time references with the factual answers, highlighting that capturing temporal misalignment in model explanations can be a critical yet overlooked issue in the current temporal alignment task.

Table 17: Example LLM responses on the temporal alignment task using the Heritage dataset, where the granularity for time accuracy is year.

[Question] Is the UNESCO heritage element "Cheoyongmu" currently inscribed or proclaimed? **[Answer]** Inscribed **[Time reference]** November 2009 (start)
[Model Response] GPT-3.5: Since Inscribed (✓) December 2011 (✗). GPT-4: Inscribed (✓) since November 2009 (✓). GPT-4o: Inscribed (✓) since November 2009 (✓). Llama3.1-70B: Inscribed (✓) since November 2009 (✓). Mixtral-8x7B: Proclaimed (✗) since December 2017 (✗). Gemma2-27B: Inscribed (✓) since November 2022 (✗). Qwen2-72B: "Cheoyongmu" has been inscribed (✓) on UNESCO's list since 2015 (✗). Granite3.1-8B: Inscribed (✓) since 2019 (✗)

Table 18: Example LLM responses on the temporal alignment task using the Netflix dataset, where the granularity for time accuracy is year.

[Question] Which director was involved in the most recent version of "Miracle in Cell No. 7"? **[Answer]** Mehmet Ada Öztekin **[Time reference]** October 2019 (start)
[Model Response] GPT-3.5: Since January 2020 (✗), the director of the latest release of "Miracle in Cell No. 7" is Mehmet Ada Öztekin (✓). GPT-4: Since March 2020 (✗), the director of the most recently released movie "Miracle in Cell No. 7" is Mehmet Ada Öztekin (✓). GPT-4o: Since October 2023 (✗), the director of the most recent "Miracle in Cell No. 7" movie is Mehmet Ada Öztekin (✓). Llama3.1-70B: Lee Hwan-kyung (✗), since January 2019 (✓). Mixtral-8x7B: Sure, since January 2019 (✓), the director of the latest release of "Miracle in Cell No. 7" is Mehmet Ada Öztekin (✓). Gemma2-27B: Since August 2023 (✗), the director of the latest release of "Miracle in Cell No. 7" is Lee Hwan-kyung (✗). Qwen2-72B: The original film was released in 2013 and a Chinese remake directed by Zhang Lü (✗) was released in January 2021 (✗). Granite3.1-8B: The most recent version of ""Miracle in Cell No. 7"" was directed by Lee Jae-gon (✗), since 2019 (✓).

D.2 INTEGRATING TIME ACCURACY TO EXISTING TSQA BENCHMARKS

Continuing from Sec. 4.1, we provide a detailed case study with Dyknow (Mousavi et al., 2024), one of the TSQA benchmarks that employs open-ended QA templates (e.g., "The president of Italy is __") (Dhingra et al., 2022; Margatina et al., 2023) to assess whether LLMs are temporally aligned with the current world.

While Dyknow evaluates LLM responses as correct (Cor.), outdated (Out.), or incorrect (Inc.) based on the parsed answer, we modify their system prompt to explicitly generate start date references to incorporate time accuracy. We then assess the correctness of each evaluation method (i.e., with and without time accuracy) against manual verification on 125 randomly sampled responses per model, where we recruit five graduate student annotators and distribute a total 1,000 responses from eight LLMs, ensuring that each response is evaluated by at least two annotators. We measure the correctness with precision (P), recall (R), and F1-score (F1), standard metrics for classification (Yacouby & Axman, 2020) with definitions provided below.

- Precision: The proportion of examples labeled as a given class (e.g., correct, outdated, and incorrect) by the evaluation method that are also judged as the same class by human annotators.

$$\text{Precision} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Positives}}$$

- Recall: The proportion of examples judged to a given class (e.g., correct, outdated, and incorrect) by human annotators that are also labeled as the same class by the evaluation method.

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives} + \text{False Negatives}}$$

- F1 Score: The harmonic mean of precision and recall, providing a balanced measure of alignment with human judgment.

$$\text{F1 Score} = 2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$

As shown in Table 19, integrating $\mathbf{T}$ consistently improves all metrics over the original method, leading to higher evaluation correctness. These results demonstrate the value of time accuracy as a complementary evaluation criterion to traditional answer accuracy. We note that the integration is straightforward for other TSQA benchmarks that employ open-ended question formats similar to Dyknow (Dhingra et al., 2022; Margatina et al., 2023), requiring only minimal prompt modifications.

Table 19: Comparison of evaluation correctness using DyKnow (Mousavi et al., 2024), with and without time accuracy ($\mathbf{T}$), against human verification.

	Methods	P	R	F1
Correct (↑)	Human	1.00	1.00	1.00
	Dyknow	0.67	0.92	0.77
	Dyknow + $\mathbf{T}$	**0.98**	**0.95**	**0.96**
Outdated (↓)	Human	1.00	1.00	1.00
	Dyknow	0.69	0.78	0.73
	Dyknow + $\mathbf{T}$	**0.95**	**0.88**	**0.91**
Incorrect (↓)	Human	1.00	1.00	1.00
	Dyknow	0.32	0.60	0.39
	Dyknow + $\mathbf{T}$	**0.58**	**0.84**	**0.64**

D.3 Temporal Span Analysis Aggregated Across Multiple Domain

Continuing from Sec. 4.2, we provide more results on temporal span analysis. In addition to Fig. 3 that shows LLM performances by temporal span evaluated on a single domain, we show aggregated results in Fig. 5 evaluated on multiple domains: Country, Athletes, and Organizations. Compared to the single domain results, LLM performances diverge more clearly, suggesting that domain-specific fluctuations are smoothed out and model-specific behaviors become more evident when multiple domains are considered. General trends – notable performance drops in recent years (2020-2025) while having performance peaks in 2010-2015 – are still observed, which are consistent with recent findings (Dhingra et al., 2022; Mousavi et al., 2024; Zhao et al., 2024).

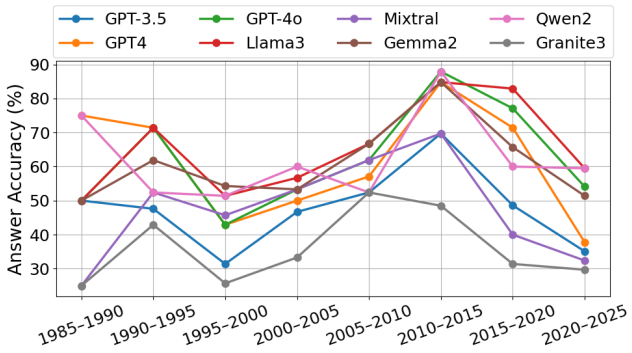


Figure 5: LLM performances across different time spans (1985-2025) in the closed-book setting, evaluated on multiple domains: Country, Athletes, and Organizations.

D.4 More Details on Experiments with Performance Improvement Techniques

Continuing from Sec. 4.3, we provide more details on experiments with performance improvement techniques: RAG (Lewis et al., 2020), CoT (Wei et al., 2022), and Time-CoT (Yin & Hu, 2024).

CoT and Time-CoT Prompts The upper and lower prompts are used for the CoT and Time-CoT settings, respectively. As illustrated, Time-CoT prompts provide more detailed intermediate steps for temporal reasoning, such as presenting relevant historical timelines (e.g., sequences of presidential terms) when compared to standard CoT.

```
Q: Who was the vice president of the host country for the 31th Summer
Olympic Games?
A: Michel Temer. The 31th Summer Olympic Games were held in August 2016
in Rio. The host country was Brazil. The Vice President of Brazil in
August 2016 was Michel Temer. The answer is Michel Temer.

Q: Can you provide the name of the governor-general of the host country
during the 27th edition of the Summer Olympics?
A: William Deane. The 27th edition of the Summer Olympics were held
in September 2000 in Sydney. The host country was Australia.
The Governor-General of Australia in September 2000 was William Deane.
The answer is William Deane.

Q: Can you identify the president of the host country for the Seoul 1988
Olympics?
A: Roh Tae-woo. The Seoul 1988 Olympics were held in September 1988.
The host country was South Korea. The president of South Korea in
September 1988 was Roh Tae-woo. The answer is Roh Tae-woo.

Q: Who held the position of general secretary in the host country during
the 1980 Olympic Games in Moscow?
A: Leonid Brezhnev. The Moscow 1980 Olympics were held in July 1980.
The host country was Soviet Union. The general secretary of Soviet Union
in July 1980 was Leonid Brezhnev. The answer is Leonid Brezhnev.
```

```
Q: Can you identify the president of the host country for the Seoul
1988 Olympics?
A: Let's think step by step. First, Seoul 1988 Olympic Games were held
in September 1988, South Korea. Then, we need to find out who was
the president of South Korea according to timeline. 1989-1993: Roh
Tae-woo, 1993-1998:Kim Young-sam. Then, we need to focus on the time
-- 1988. So we can obtain the answer is Roh Tae-woo.
Therefore, the answer is Roh Tae-woo.

Q: Who held the position of general secretary in the host country during
```

```
the 1980 Olympic Games in Moscow?
A: Let's think step by step. First, Moscow 1980 Olympic Games were
held in July 1980, Soviet Union. Then, we need to find out who was
the general secretary of Soviet Union according to timeline. 1964-1982:
Leonid Brezhnev, 1982-1984: Yuri Andropov. Then, we need to focus on
the time -- 1980. So we can obtain the answer is Leonid Brezhnev.
Therefore, the answer is Leonid Brezhnev.

Q: What is the name of the monarch of the host country for the Oslo 1952
Olympic Games?
A: Let's think step by step. First, Oslo 1952 Olympic Games were held
in February 1952, Norway. Then, we need to find out who was the monarch
of Norway according to timeline. 1905-1957: Haakon VII, 1957-1991: Olav
V. Then, we need to focus on the time -- 1952. So we can obtain the
answer is Haakon VII. Therefore, the answer is Haakon VII.

Q: Which emperor was in charge of the host country during the Sapporo
1972 Olympic Games?
A: Let's think step by step. First, Sapporo 1972 Olympic Games were
held in February 1972, Japan. Then, we need to find out who was the
president of Japan according to timeline. 1926-1989: Showa, 1989-2019:
Akihito. Then, we need to focus on the time -- 1972. So we can obtain
the answer is Showa. Therefore, the answer is Showa.
```

Case Study of Temporally Misaligned RAG We observe that standard RAG methods often fail to account for temporal cues embedded in the question. Table 20 and Table 21 present illustrative examples of such temporal misalignments, where retrieved documents from Wikipedia describe the Olympics from incorrect time periods or provide generic explanations of the Olympics.

Table 20: Retrieved Wikipedia passage describing the 1964 Winter Olympics, given the question asking about the 7th Winter Olympics (held in 1956).

[Question] Who was the president of the host country for the 7th Winter Olympic Games?
[Retrieved Document] The 1964 Winter Olympics, officially known as the IX Olympic Winter Games (German: IX. Olympische Winterspiele) and commonly known as Innsbruck 1964 (Austro-Bavarian: Innschbruck 1964), were a winter multi-sport event which was celebrated in Innsbruck, Austria, from January 29 to February 9, 1964. ...

Table 21: Retrieved Wikipedia passage describing generic information about the Olympics, given the question asking about the 4th Summer Olympics.

[Question] Who was the Prime Minister of the host country during the 4th edition of the Summer Olympic Games?
[Retrieved Document] The modern Olympic Games (Olympics; French: Jeux olympiques) are the world's leading international sporting events. They feature summer and winter sports competitions in which thousands of athletes from around the world participate in a variety of competitions. The Olympic Games are considered the world's foremost sports competition, with more than 200 teams, representing sovereign states and territories, participating. ...

Results on the Single-hop Setting In addition to the multi-hop setting presented in the main text (Table 7), we provide more results on single-hop questions. Specifically, we apply the same performance improvement techniques to the questions used in the temporal reasoning task (Sec. 4.2) under the closed-book setting to examine the effectiveness of each technique – RAG for providing up-to-date knowledge, and CoT and Time-CoT for improving temporal reasoning – and report the results in Table 22. Interestingly, all techniques greatly improve performances on None-type questions, where we observe that models tend to respond with "no answer" more frequently, possibly rejecting to respond if they are uncertain for their reasoning. In addition, when the additional contexts retrieved via RAG do not contain the gold answer – due to the temporal misalignment issue discussed above – we also observe that models tend to respond with "no answer" rather than relying on their own

knowledge, which degrades performances on Multiple- and Unique-type questions while improving performance on None-type questions. As with the multi-hop results, we observe similar performance between CoT and Time-CoT in the single-hop setting.

Table 22: Comparison of LLM performances with different performance improvement techniques – RAG, CoT, and Time-CoT – across question types categorized by answer cardinality: Multiple, Unique, and None, evaluated on the Wikipedia dataset under the closed-book setting. The results are compared with the original setting (Orig.). We report **AT** for Multiple and Unique types, and **A** for the None-type, as no time reference applies to no-answer cases.

	Multiple				Unique				None			
Model	**Orig.**	**RAG**	**CoT**	**Time-CoT**	**Orig.**	**RAG**	**CoT**	**Time-CoT**	**Orig.**	**RAG**	**CoT**	**Time-CoT**
GPT-3.5	12.4	14.2	9.0	0.4	38.7	26.6	26.6	12.7	56.8	54.2	83.9	97.1
GPT-4	20.2	25.1	21.0	30.0	61.3	54.3	65.9	57.3	19.0	39.6	51.6	74.7
GPT-4o	34.5	30.7	24.3	32.6	65.1	59.2	62.9	62.9	37.4	43.2	60.4	50.2
Llama3.1-70B	20.6	8.6	16.5	19.9	59.4	34.5	68.9	48.7	22.0	54.9	25.3	33.3
Mixtral-8x7B	10.9	9.7	8.6	15.4	40.6	30.3	50.9	48.7	28.9	16.5	30.8	26.7
Gemma2-27B	24.3	13.9	19.9	21.3	59.4	45.7	62.2	62.5	6.2	16.8	10.6	12.1
Qwen2-72B	19.1	17.2	13.5	12.7	57.5	51.7	59.2	59.9	20.1	32.6	38.8	39.6
Granite3.1-8B	6.7	4.9	4.9	7.1	34.1	15.7	22.8	20.6	20.9	43.6	76.9	60.1

D.5 More Details on Correctness Analysis

Continuing from Sec. 4.4, we provide a more fine-grained correctness analysis result. Similarly to the manual verification setup in Sec. D.2, we manually verify 125 randomly sampled responses per task and measure the correctness using precision, recall, and F1 score. As shown in Table 23, TDBench exhibits high agreement with manual verification, achieving higher precision than recall. This result indicates that TDBench can effectively capture responses with both correct answers and valid temporal reasoning, while some incorrect explanations – particularly those unrelated to temporal references – remain challenging to detect.

Table 23: Correctness of TDBench against manual verification across question subcategories, measured with Precision, Recall, and F1 score – see metric definitions in Sec. D.2.

Task	**P**	**R**	**F1**
Temporal alignment (Average)	0.98	0.96	0.97
Temporal reasoning (Multiple)	0.85	0.88	0.86
Temporal reasoning (Unique)	0.81	0.87	0.83
Temporal reasoning (None)	0.89	0.90	0.90
Temporal reasoning (Average)	0.87	0.91	0.88
Multi-hop (Average)	0.95	0.87	0.91

D.6 Evaluation on Synthetic Medical Data

Continuing from Sec. 4.5, we demonstrate how TDBench can be applied to synthetic datasets, as long as the underlying tables used in TDBench have TFDs satisfied. We use a synthetic medical dataset consisting of synthetic records of patients at a hospital, and ask questions about doctors and medication by using TFDs *name, gender, blood_type* $\xrightarrow{T}$ *doctor* and *name, gender, blood_type* $\xrightarrow{T}$ *medication* – see example questions in Sec. C.2.

Table 24 shows improved LLMs performances compared to the performances on real-world factual questions, particularly for Multiple- and None-type questions. We hypothesize that this improvement may stem from reduced interference by the model's internal knowledge. As the data is synthetic and unfamiliar, models are more likely to focus on the explicit temporal context provided in the prompt, potentially leading to more accurate temporal reasoning.

Table 24: Comparison of LLM performances across question types categorized by answer cardinality: Multiple, Unique, and None, evaluated on the synthetic Medical dataset in the open-book setting. We report only **A** for the None-type, as no time reference applies to no-answer cases.

	Multiple			Unique			None
Model	**A**	**T**	**AT**	**A**	**T**	**AT**	**A**
GPT-3.5	97.5	50.4	61.9	35.4	93.6	33.0	**100.0**
GPT-4	**98.8**	77.9	77.7	44.4	**98.6**	43.9	91.0
GPT-4o	97.5	**78.6**	78.5	**59.8**	97.2	**58.4**	**100.0**
Llama3.1-70B	95.8	68.6	**85.8**	57.9	76.6	56.4	98.8
Mixtral-8x7B	97.1	55.7	60.8	24.9	90.6	22.9	27.1
Gemma2-27B	94.8	52.1	78.3	48.3	89.8	47.0	**100.0**
Qwen2-72B	93.5	68.9	66.2	53.5	95.1	52.2	**100.0**
Granite3.1-8B	88.3	44.8	41.5	17.6	93.5	17.1	**100.0**

D.7 Evaluation of Task-specific TSQA Methods

Continuing from Sec. 4.5, we provide an additional analysis with task-specific TSQA methods. While the primary goal of our study is to assess the accuracy and reliability of general-purpose models – those expected to possess "accurate knowledge" and widely adopted in many tasks as GPT-Judges for handling factual knowledge (Lin et al., 2021; Sun et al., 2023; Wang et al., 2023) – performance analysis on task-specific models such as TG-LLM (Xiong et al., 2024) and TempT5 (Tan et al., 2023) can offer insights in different perspectives. Specifically, we aim to explore (1) performance differences compared to general-purpose models and (2) the effectiveness of their training methods when measured with other TSQA pairs beyond the original benchmarks used for their training (TGQA (Xiong et al., 2024) and TempREASON (Tan et al., 2023) for TG-LLM and TempT5, respectively), which follow different QA styles.

Table 25: Performance comparison of task-specific TSQA methods. Only **A** is reported for TempT5 and T5 due to their answer-only format.

Model	**A**	**AT**
Llama3.1-70B	58.4	54.2
Mixtral-8x7B	42.9	30.9
Gemma2-27B	69.3	32.8
TG-LLM	41.0	34.0
Llama2-13B (base model of TG-LLM)	37.0	27.0
TempT5	4.2	N/A
T5-base (base model of TempT5)	0.0	N/A

As shown in Table 25, TG-LLM demonstrates a notable performance improvement over its base model (i.e., Llama2-13B) and performs comparably to the general purpose model Gemma2-27B; however, the performance still lags behind the larger Llama family model used in our experiments (i.e., Llama3.1-70B). In contrast to the good generalization ability shown in TG-LLM, TempT5 greatly struggles with TDBench's QA pairs, resulting in low performance, likely due to the limited capacity of its underlying architecture (i.e., T5-base).

D.8 Comparison with LLM-based Methods

Continuing from Sec. 3.1 and Sec. 4.5, we provide a case study comparing TDBench with LLM-based methods. While TDBench leverages both database techniques and an LLM for TSQA construction, one possible approach is to solely use LLMs to directly generate QA pairs from an input data source (Kim et al., 2024; Zhao et al., 2024). We demonstrate how this LLM-only approach can (1) be more prone to hallucinations and (2) incur higher inference costs when processing the raw data.

Anlaysis on Hallucination We demonstrate with Zhao et al. (2024), using their system prompt, shown below. To better reflect realistic multi-attribute reasoning scenarios, we relax one constraint in the original prompt: each question should contain only one column's information.

```
Below is a table in CSV format separated with commas ‘,’. Based on this
table’s information along with its description and abstracts,
please raise up to ten questions that the answers are different
in 2010, 2019, and 2023. After raising the question, please get answers
for those time points from the table. Please make sure the answers
should be totally different without overlapping. Please only raise
questions regarding the latest status of those time points instead of
the history, while also do not explicitly mention the time information
in the question to make them more natural. Do not ask questions
cannot be answered based on the information provided in the table. Make
sure the full and explicit names of related entities are used in
the question based on the description in the prompt and do not use
pronouns.
```

We use the same LLM (GPT-4) as in their study and provide 50 rows from the *Country* dataset. The generated QA pairs are as follows:

- Q_1: What name was associated with the role of the Prime Minister of Australia?
  A_1: Anthony Albanese
- Q_2: Who was the Prime Minister of Denmark in 2010?
  A_2: Lars Løkke Rasmussen
- Q_3: Who was the Prime Minister of Denmark in 2019?
  A_3: Lars Løkke Rasmussen
- Q_4: Who was serving as the President of Nigeria in the year when Goodluck Jonathan started his term?
  A_4: Goodluck Jonathan
- Q_5: Who was serving as the Prime Minister of Denmark when Mette Frederiksen began her term?
  A_5: Mette Frederiksen

While the model correctly identifies the time-sensitive column based on the table schema (e.g., the name of the role-holder), the generated QA pairs do not fully adhere to the instructions. For instance, (Q_2, A_2) and (Q_3, A_3) explicitly mention temporal information, violating the guideline to avoid doing so; (Q_2, A_2) and (Q_3, A_3) makes it easy to infer answers from the questions themselves, compromising the question quality.

This case study indicates that LLM-based QA generation can result in less controlled QA generation, being vulnerable to hallucinations even when the provided data source is relatively in small-scale (i.e., 50 rows). In contrast, SQL-based data processing employed in TDBench can ensure more controlled QA generation, even at scale, thereby reducing the manual effort often required in LLM-based methods to identify and eliminate hallucinated responses (Kim et al., 2024; Wu et al., 2024).

Analysis on Inference Cost More importantly, SQL-based processing can be more cost-effective. TDBench only uses the necessary attributes for generating questions via TFDs and discards the rest, whereas an LLM-only approach typically ingests an entire row. We compare TDBench with an LLM-only baseline on five datasets used in our experiments (Sec. 4). As a result, Table xx shows that TDBench uses significantly fewer input tokens while achieving comparable inference time as that of the LLM-only baseline. We also observe greater cost benefits in larger, real-world datasets like the Netflix dataset compared to smaller, well-processed datasets like the Leaders dataset, demonstrating the scalability of TDBench.

Table 26: Comparison of inference time (Time (s)) and input size (Tokens) across datasets, where each dataset's column count (#col) is shown. Bold indicates the lower (better) value.

	Leaders (#col: 5)		**Olympic** (#col: 7)		**Environ** (#col: 10)		**Medical** (#col: 15)		**Netflix** (#col: 18)	
Model	*Time (s)*	*Tokens*	*Time (s)*	*Tokens*	*Time (s)*	*Tokens*	*Time (s)*	*Tokens*	*Time (s)*	*Tokens*
LLM-only	1.79	206	**1.89**	316	**1.47**	376	**1.81**	542	1.91	1,288
TDBench	**1.62**	**161**	2.57	**177**	1.93	**169**	3.32	**299**	**1.73**	**138**

D.9 FULL EXPERIMENTAL RESULTS

Continuing from Sec. 4.3, we provide full results on the multi-hop setting. Table 27 shows that Llama3.1-70B outperforms GPT-4o in the 2-hop setting, whereas GPT-4o outperforms Llama3.1-70B in the 3-hop setting. Interestingly, GPT-4o shows an extremely low hallucination rate (i.e., $\mathbf{H}_1$) in the 2-hop setting – which requires identifying the role-holder of the host country of a given Olympic games – indicating that once the model get the correct host country and time, the model is mostly able to retrieve the correct role-holder for that time.

Table 27: Performance comparison on multi-hop questions where $\mathbf{H_i}$ denotes the hallucination rate at the $(i+1)$-st hop given that the i-th hop is correct.

	2-hop			3-hop			
Model	**A**	**AT**	$\mathbf{H_1}$	**A**	**AT**	$\mathbf{H_1}$	$\mathbf{H_2}$
GPT-3.5	66.7	63.1	9.1	33.8	33.8	**8.5**	7.6
GPT-4	88.4	67.2	4.5	57.1	52.5	10.8	0.5
GPT-4o	86.9	79.3	**0.0**	**90.4**	**87.9**	26.3	**0.0**
Llama3.1-70B	**91.9**	**83.8**	68.8	82.8	80.8	38.2	4.5
Mixtral-8x7B	80.8	72.7	45.9	60.1	49.0	19.5	10.6
Gemma2-27B	79.8	77.8	35.1	48.0	43.9	26.5	24.7
Qwen2-72B	78.3	65.2	50.0	68.2	59.1	35.1	5.6
Granite3.1-8B	73.7	50.5	80.4	11.1	11.1	10.3	77.8