DateLogicQA: Benchmarking Temporal Biases in Large Language Models

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Abstract

This paper introduces DateLogicQA, a benchmark with 190 questions covering diverse date formats, temporal contexts, and reasoning types. We propose the Semantic Integrity Metric to assess tokenization quality and analyse two biases: Representation-Level Bias, affecting embeddings, and Logical-Level Bias, influencing reasoning outputs. Our findings provide a comprehensive evaluation of LLMs' capabilities and limitations in temporal reasoning, highlighting key challenges in handling temporal data accurately. The GitHub repository for our work is available at https://github.com/gagan3012/EAIS-Temporal-Bias [1]

1 Introduction

Accurate temporal reasoning is essential for real-world applications like event planning and historical questions. However, biases in Large Language Models (LLMs) can lead to misinterpretations or errors in date-related tasks. Understanding these biases is essential for precisely handling numerical structures and contextual meanings, making temporal reasoning ideal for identifying and analysing biases in tokenization, representation, and logical reasoning.

A significant source of these biases originates from the tokenization process. While tokenizers divide the text into subword units, inconsistencies in tokenizing dates can disrupt reasoning tasks. This can lead to two types of biases: Representation-Level Bias, caused by inconsistencies in embeddings affecting semantic structures of dates, and Logical-Level Bias, where correct tokens do not yield accurate outputs due to misaligned internal processing. Together, these biases highlight the challenges LLMs face in preserving the integrity and interpretability of temporal data across diverse formats and contexts.

[1] ϕ Denotes equal contribution

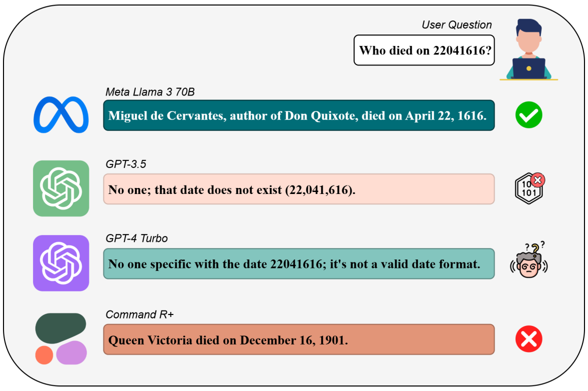


Figure 1: Examples of temporal biases in LLMs. **Incorrect** Response, **Faulty Date** but accurate reasoning indicating representation level temporal bias, **Faulty reasoning** but accurate date indicating logical level temporal bias, **Correct** response

This paper makes several contributions to understanding temporal biases in LLMs. **(1)** We introduce **DateLogicQA**, a dataset of 190 curated questions for evaluating temporal reasoning across various date formats, contexts (past, present, future), and reasoning types (commonsense, factual, conceptual, numerical). **(2)** We propose the Semantic Integrity Metric to assess tokenization quality, punishing unnecessary splits and excessive token counts. **(3)** We conduct human evaluations of model responses to analyse tokenization accuracy and reasoning quality, providing insights beyond automated metrics. **(4)** A thorough bias evaluation examines representation and logical-level biases using embeddings and outputs to investigate LLMs' treatment of temporal references.

We have organised the paper as follows: Section 2 reviews related works, summarising the impact of tokenization on LLM performance and past temporal reasoning approaches. Section 3 details the creation of the DateLogicQA dataset, including its design principles and examples. Section 4 outlines methods for evaluating tokenization, temporal reasoning, and biases. Section 5 presents experiment results, followed by a discussion of findings and bias mitigation in Section 6. Lastly, Section 7 summarises our contributions.

2 Related Works

Impact of Tokenization on Language Models Tokenization significantly affects the efficiency and reasoning abilities of large language models (LLMs). Research by Gu et al. (2024) and Goldman et al. (2024) highlights that tokenizers with higher compression rates enhance representation efficiency, particularly in smaller models. However, Schmidt et al. (2024) argue that effective tokenization also depends on pre-tokenization and vocabulary design. Studies like Ahia et al. (2023) show that poorly tokenized languages face performance and fairness issues. Furthermore, choices in tokenization impact reasoning; Zhang et al. (2024) and Singh and Strouse (2024) indicate that numerical tokenization can lead to errors in arithmetic and counting tasks. Rajaraman et al. (2024), Alberts et al. (2024), Minixhofer et al. (2024), and Gastaldi et al. (2024) show how well-designed tokenizers improve sequence pattern modelling and numerical reasoning through advanced embedding methods. Our study extends this work by examining tokenization's role in handling diverse date formats for temporal reasoning.

Temporal Reasoning in LLMs Temporal reasoning poses challenges for LLMs due to inherent biases. Zhu et al. (2024) discussed "nostalgia bias" (favouring outdated knowledge) and "neophilia bias" (speculative future predictions), while Tan et al. (2023b) observed inconsistent generalisation across different time periods. Structured approaches like temporal graphs (Xiong et al., 2024a) and synthetic datasets (Fatemi et al., 2024) enhance performance by explicitly encoding temporal relationships. Additionally, tokenization critically affects temporal reasoning; Zhao et al. (2024) found that temporal misalignment hampers accuracy, and Kishore and He (2024) identified inductive biases in models like GPT-3.5 and GPT-4. Su et al. (2024a) propose task-agnostic approaches to enhance temporal reasoning, while Gastaldi et al. (2024) and Rajaraman et al. (2024) link tokenization to reasoning performance. By analysing how tokenization strategies affect temporal reasoning, especially for date formats, our work fills a gap in understanding the interplay between tokenization and temporal task performance.

3 DateLogicQA

We introduce **DateLogicQA**, a dataset designed to explore how LLMs handle dates in various formats and contexts to tokenize, interpret, and reason with them. It consists of 190 questions divided into four categories: *commonsense*, *factual*, *conceptual*, and *numerical*. Each category features one of seven date formats across three temporal contexts: *past*, *present*, and *future*. This systematic variation allows for an in-depth analysis of LLMs' performance with temporal information.

Objective and Purpose The dataset aims to assess LLMs' tokenization and understanding of dates, as errors can lead to interpretative biases. By embedding dates within questions, we evaluate context-rich date interpretation, simulate real-world scenarios where dates carry contextual significance, and test LLMs' ability to extract and interpret date information accurately.

Concepts	Example
Numerical	What is the time 7 years and 9 months after 27101446?
Factual	Which of the people died on 23041616? A) Shah Jahan B) Miguel de Cervantes C) Princess Diana D) William Shakespeare
Conceptual	The first iPhone was released on 29062007. How many years has it been since its release?
Commonsense	John was born on 15-03-1985. He graduated from college on 01-05-2007. Was John older than 18 when he graduated?

Table 1: Dataset samples illustrating different temporal reasoning concepts.

Date Format	Example
DDMMYYYY	23041616
MMDDYYYY	04231616
DDMonYYYY	23April1616
DD-MM-YY	23-04-16
YYYY, Mon DD	1616, April 23
DD/YYYY (Julian calendar)	113/1616
YYYY/DD (Julian calendar)	1616/113

Table 2: Dataset samples illustrating different date formats used.

This approach comprehensively examines various temporal notations, including uncommon formats like Julian calendar representations.

Temporal Distribution DateLogicQA spans a broad temporal range, featuring dates from historical periods (e.g., the 1600s), modern contexts (e.g., the 2000s), and hypothetical futures (e.g., the 2100s). For clarity, we categorised dates into *past*, *present*, and *future*, with some questions covering multiple dates to assess LLMs' ability to manage temporal relationships across contexts.

Rationale for Design The dataset prioritises models' ability to interpret dates within broader narratives rather than as isolated data points. Its smaller size allows for careful curation of high-quality, linguistically diverse questions, focusing on specific nuances of temporal reasoning. This enables detailed analysis of model behaviour and understanding of temporal biases.

4 Methodology

The study proposes three interests to investigate temporal bias in models: tokenization process, temporal task capability, and internal computation across different LLMs.

4.1 Semantic Integrity

This experiment targets the tokenization process in different LLMs to identify how it influences the semantic interpretation of dates when presented in different formats. We specifically focus on the Semantic Integrity Metric, which measures the extent to which the original semantic meaning of a date is preserved after tokenization. Several key highlights are observed, such as how a single date input is presented after being tokenized, the extent of semantic preservation, and the ability to generalise across different date representations. These findings provide valuable insights into the tokenization process and its impact on temporal reasoning in LLMs.

Semantic integrity evaluates how well the tokenized date output maintains its original meaning and structure. The semantic integrity score ranges from 0 to 1. A higher score - closer to 1 - indicates that the date segmentation is nearly accurate, better preserving the intended structure and information. In contrast, a score closer to 0 indicates an inadequately tokenized date structure. The formula for calculating semantic integrity is as follows:

$$\mathrm{SI} = \max\left(0, \min\left(1, 1 - P - S - T - R\right)\right)$$

		Reasoning	
		Wrong	Correct
Date	Wrong	Incorrect (Hallucination)	Faulty Date, Accurate Reasoning (Representation-Level Temporal Bias)
	Correct	Accurate Date, Faulty Reasoning (Logical-Level Temporal Bias)	Correct

Figure 2: Human evaluation rubric

Unnecessary Splitting of Components (P) : If a date is tokenized into parts that do not correspond to the ideal format, a penalty of 0.1 is applied.

Preservation of Separators (S) : A penalty of 0.1 is applied when separators are lost during tokenization, reflecting incorrect date parsing (e.g., tokenizing `%Y-%m-%d` as `%Y%m%d`).

Token Count (T) This penalty design aims to penalise token outputs longer than necessary, such as `%Y-%m-%d`. If any tokenized output exceeds five splits, we apply a penalty for excessive fragmentation. A higher token count often indicates a loss of semantic information, hindering the model's ability to interpret temporal values.

Similarity with Baseline (R) This metric uses cosine similarity to measure how much a tokenized output deviates from a baseline reference of date tokens. Tokens with greater deviation incur higher penalties, while those resembling the baseline receive lower penalties.

4.2 Human-Led Temporal Bias Assessment

Understanding temporal contexts is crucial for analysing events over time. This includes grasping temporal references like *"How many years has it been since..."* (Past) and *"What will the contract's last day be..."* (Future), along with the maintenance of logical chronological order and adaptation to changes in context. For large language models, this capability is vital for tasks such as historical inquiries, time-sensitive query handling and predictions about future events. Assessing biases in temporal reasoning is essential for accuracy across various applications. We utilized the dataset referenced in Section 3.

We conduct a human evaluation to assess the temporal bias of LLMs as automated methods may exhibit inherent biases that affect results, ultimately undermining the evaluation's purpose. This methodology provides a more reliable analysis, identifying outliers that respond accurately without fully comprehending temporal aspects. Instead, it relies on contextual clues or learned patterns acquired during training or through retrieval-augmented generation.

Model responses are categorised based on colours in Figure 2, representing levels of temporal understanding. **Dark Orange** (■) denotes incorrect answers or temporal hallucinations from failure to tokenize dates or grasp context. **Light Orange** (■) reflects Representation-Level Temporal Bias, where the model tokenizes dates inaccurately but reaches the correct answer through logical reasoning. This suggests that some internal reasoning within the model compensates for misunderstanding the date format. **Light Teal** (■) signifies Logical-Level Temporal Bias, where the model tokenizes correctly but misapplies logic due to misattributing events or calculation errors. Finally, **Dark Teal** (■) denotes correct answers, indicating successful tokenization and logical reasoning. This illustrates a complete understanding of the question.

4.3 Understanding Temporal Bias

We investigate potential biases in the internal embedding space and softmax computations of large language models (LLMs) when processing texts with different temporal references, such as past, present, and future contexts. Temporal biases in LLMs fall into two main types: **Representation-Level Temporal Bias** indicates significant differences in internal embeddings across time references, revealing inconsistencies in encoding semantic information. In contrast, **Logical-Level Temporal Bias** occurs when output probabilities vary for semantically identical inputs due to changes in temporal references.

We established a controlled experimental framework to quantify these biases, analysing embeddings and softmax outputs across three temporal categories: *past*, *present*, and *future*. We measured representation-level biases using cosine similarity between averaged embeddings, with lower similarity indicating greater divergence. We assessed logical-level biases using KL divergence for softmax distributions, where higher divergence reflects substantial probability differences. Additionally, we examined sensitivity to seven date formats from Table 2.

We conducted experiments using *Llama 3.2 3B* (Dubey et al., 2024). For each prompt, we extracted two key outputs: internal embeddings, averaged from all the hidden layers of hidden states, and softmax probabilities, denoting the output distribution over the vocabulary. We analysed temporal biases by comparing these outputs across different references. Simultaneously, we assessed format sensitivity within each reference to determine how tokenization and variations in date formats affect model behaviour.

5 Results

5.1 Impact of tokenizers

Model	SI	TC	PC	PS
Baseline	1.00	4.30	✓	✓
OLMoE	0.77	5.08	≈	✓
OLMo	0.77	5.08	≈	✓
Davinci-003	0.75	5.17	×	✓
Llama 3	0.74	4.98	×	✓
GPT-3.5	0.74	4.98	×	✓
GPT-4	0.74	4.98	×	✓
GPT-4o	0.74	4.98	×	✓
Qwen	0.42	9.30	×	✓
Cohere	0.42	9.30	×	✓
Gemma	0.42	9.30	×	✓
DeepSeek	0.42	9.30	×	✓
Llama 2	0.37	10.30	×	✓
Mistral	0.37	10.30	×	✓
Phi 3.5	0.37	10.30	×	✓
Llama 1	0.37	10.30	×	✓

Table 3: Performance comparison of various models on semantic integrity, token count, and preservation of components and separators.

In Table 3, we present the Semantic Integrity scores with respect to token count **(TC)**, component preservation **(PC)** and separators **(PS)** for different tokenizers used by the tested models. Notably, newer released models tend to have a higher average semantic integrity score at ≈ 0.7 while token counts maintained close to the frequency of ≈ 5.

As described in Table 2, most of the tested date formats are composed of 5 components (e.g., DD-MM-YY), with some instances of a 3-component structure like the Julian date format (YYYY/DD). As a result, the baseline reference has an average token count of 4.30 rather than the ideal 5.

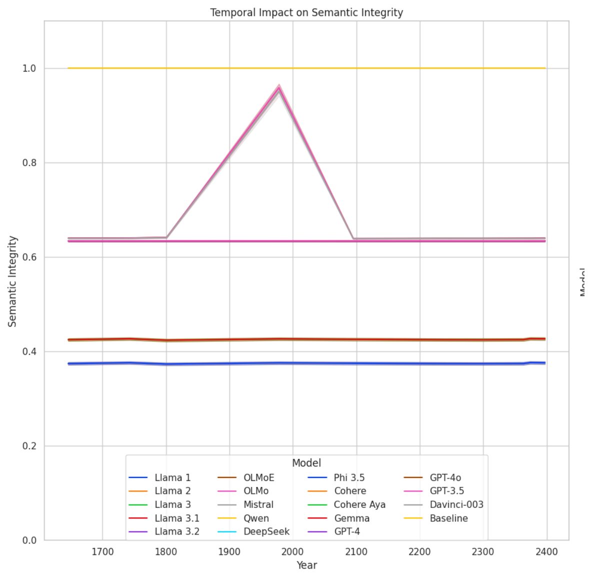


Figure 3: Temporal impact on semantic integrity

While many tokenizers struggled to consistently preserve the components, often producing tokenized outputs that deviated from the ideal, the tokenizers used by the OLMoE (Muennighoff et al., 2024) and OLMo (Groeneveld et al., 2024) models handled date inputs correctly on certain occasions.

Token Count and Semantic Integrity From Table 3, we identify an indirect relationship between the token count and the Semantic Integrity score, specifically at lower Semantic Integrity often corresponds to more token splits, suggesting that excessive and inefficient token splitting could badly impact the interpretability of the original input. Figure 8 further establishes this observation by showing that the Semantic Integrity scores tend to fall near the lower end in the area of higher token count.

Shared Characteristics Between Tokenizers Results produced by some tokenizers have been identical, as observed in Table 3. For example, the tokenizers that Llama 1 (Touvron et al., 2023a) and Mistral (Jiang et al., 2023) use produce similar Semantic Integrity scores, a trend also observed in other models. Therefore, we investigated this further by evaluating the output from the tokenizers used by all models, presenting the results in Table 4. This finding seems accurate, as we identified similar tokenized date outputs from the tokenizers used in certain models. For instance, (Macijauskas, 2024) has also concluded a similar finding for the tokenizer used by GPT-4 (OpenAI et al., 2023) and Llama 3 (Dubey et al., 2024), which both produced similar outputs during his experiment. From our observation, this helps justify the idea of shared tokenizers between several models.

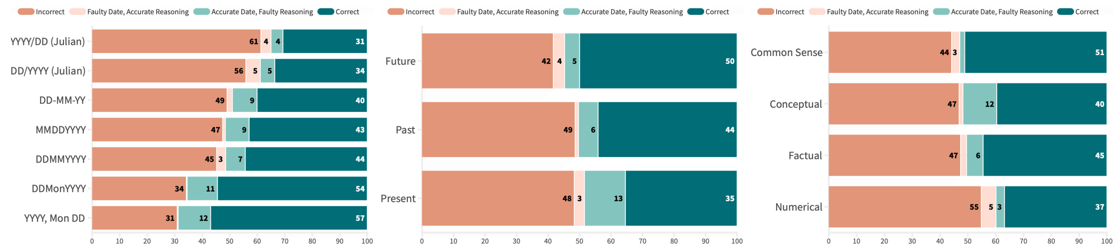
Performance in Different Temporal References In addition, Figure 3 reveals that certain tokenizers exhibit a temporal bias, resulting in varying scores produced in different timelines. Some tokenizers yield better Semantic Integrity scores for dates closer to the present (1900s-2100s). Although this is not consistently true across all tokenizers, this pattern highlights a potential bias in a tokenizer, with some favouring more recent dates over others. Slight variations in Semantic Integrity scores are particularly noticeable between the 1700s and 1900s for the tokenizers from Gemma (Team et al., 2024) and Phi 3.5 (Abdin et al., 2024) model. In contrast, the tokenizers used by OLMoE (Muennighoff et al., 2024) and OLMo (Groeneveld et al., 2024) exhibited more significant score fluctuations in more recent years.

5.2 Temporal Reasoning Analysis

Temporal reasoning, including processing and drawing inferences from historical and future dates, is one of the most challenging tasks for large language models. The current study investigates whether there are any differences in LLM performance when reasoning with historical dates, such as "July 20, 1969", and future dates, such as "January 1, 2050". To this end, we present the testing of 12 state-of-the-art LLMs using a question-answer dataset encompassing different date formats and various temporal contexts. This paper examines their skills in tokenization, comprehension, and inference on dates. We classify the answers into four categories based on their accuracy and treatment of the dates and logical structure involved, thereby providing a systematic evaluation framework.

In order to ensure that the assessment is robust, four human annotators, each with at least four years of experience in computer science, evaluated the responses across the four categories. The labelling achieved a high inter-annotator agreement with a Cohen's kappa (K) score of 0.80, confirming the reliability of the evaluation framework. These results evidence two critical areas where LLMs shine and their struggles, giving further information about their strengths and limitations concerning temporal reasoning.

Performance of Selected LLMs The evaluation of 12 language models, accessed through Hugging



(a) Date Format visualisation (b) Time period visualisation (c) Question Type visualisation

Figure 4: Results Visualisations

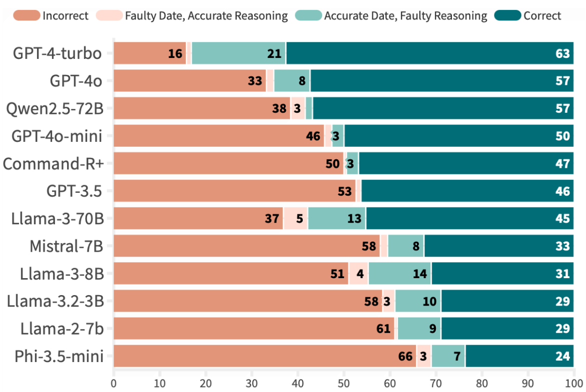


Figure 5: Each bar is segmented into four colors representing the quality of responses: **Incorrect** Response, **Faulty Date** but accurate reasoning indicating representation level temporal bias, **Faulty reasoning** but accurate date indicating logical level temporal bias, **Correct** response

Face and OpenAI APIs, provided a comprehensive overview of their performance on temporal reasoning tasks. Small models like Llama-3.2-3B (Dubey et al., 2024) and Phi-3.5-mini (Abdin et al., 2024) gave bad performances, with 58% and 66% incorrect answers, respectively. Due to their restricted processing and resources, these models performed poorly in tokenization and reasoning. Mid-sized models, including Mistral-7B (Jiang et al., 2023), Llama-3-8B (Dubey et al., 2024), and Llama-2-7B (Touvron et al., 2023b), demonstrated a more moderate improvement. They had trouble with complex reasoning problems, although they were able to improve their tokenization accuracy. Larger models, including Llama-3-70B (Dubey et al., 2024), Qwen2.5-72B (Yang et al., 2024), and Command R+ (Cohere, 2024), were more robust in their performance, especially in date interpretation and logical reasoning. However, there were inconsistencies in specific formats. Proprietary models, including GPT-3.5 (Brown et al., 2020), GPT-4-turbo (OpenAI et al., 2023), GPT-4o, and GPT-4o-mini (OpenAI et al., 2024) outperformed all the rest, with GPT-4-turbo leading on correct responses with 63% and the lowest rate of incorrect answers at 16%. These results emphasise that model size, architecture, and diversity of pretraining data all bear on performance related to temporal reasoning tasks.

Performance Based on Date Formats The format of the date had a significant impact on model performance. Models performed best for formats that included clear separators and natural language cues, such as "YYYY, Mon DD" with 57% correct and "DDMonYYYY" with 54% correct. The poorest performance was from formats like "YYYY/DD (Julian)" and "DD/YYYY (Julian)", with only 31% and 34% correct, respectively, since the representation is less common and more complex in tokenization. This trend indicates format standardisation's apparent relevance in improving date processing efficiency in LLMs.

Performance Across Temporal Contexts Temporal context also mattered a lot. Models were better with future dates, 50% correct, compared to historical dates, 44%, and present dates, 35%. This runs contrary to the expectations and may point to the fact that future-oriented reasoning tasks tap into the generative and predictive capabilities of the models. Historical and present contexts, which often require exact recall or conformity to training data, proved more difficult due to inconsistencies in the coverage of pretraining corpora.

Performance by Question Type Question type further modified results, with commonsense reasoning questions reaching the highest percentage of correctness: 51%. These questions depended less on explicit tokenization and more on logical inference, which LLMs did comparatively well. Factual questions were at 45%, while conceptual questions reached slightly lower performances of 40%. Numerical reasoning questions were the hardest; only

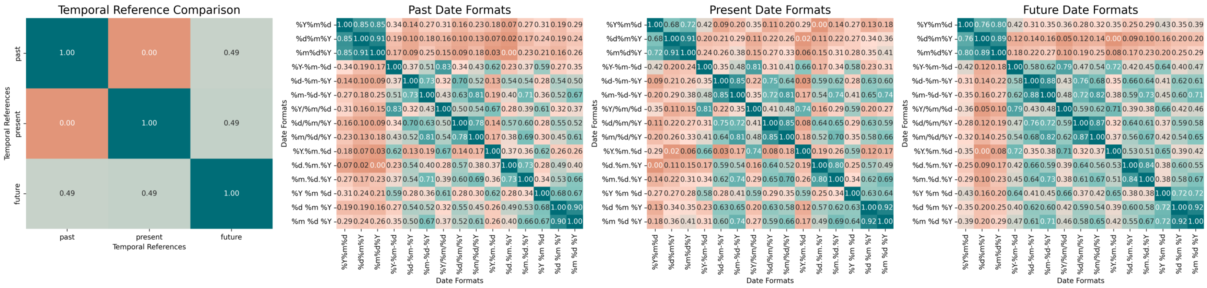


Figure 6: Representation level Temporal Bias Analysis using LLama 3.2 3B

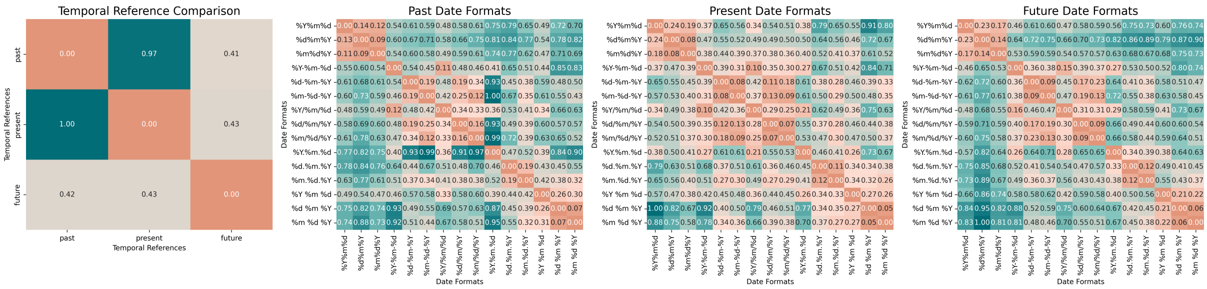


Figure 7: Logical level Temporal Bias Analysis using LLama 3.2 3B

37% were correct since these often included some calculation or logical deduction that exposed the weaknesses in the models' reasoning capability.

5.3 Temporal Sensitivity Analysis

We analyse temporal biases and format sensitivity by examining the embeddings and softmax outputs of the model for prompts across three temporal categories — past, present, and future — and multiple date formats, as shown in Table 2. We organise the findings into representation-level bias, logical-level bias, and format sensitivity, and we show the results in Figure 6 and Figure 7.

Representation-Level Bias We evaluated representation-level bias by calculating the cosine similarity between the averaged embeddings for prompts across the three temporal references. The leftmost heatmap in Figure 6 illustrates these similarities.

The embeddings for past and present references exhibit no measurable similarity (0.00), emphasising that the model encodes historical and contemporary contexts with distinct semantic structures. However, the moderate similarity between future and present suggests some shared contextual features between these categories while maintaining semantic differentiation. The moderate similarity between past and future indicates that these categories share overlapping contextual features while remaining semantically distinct. This further implies that the model is somewhat confused regarding futuristic references, which may frequently misattribute to a different temporal category, likely reflecting the training data distribution.

Logical-Level Bias We assessed logical-level bias by measuring the Kullback-Leibler (KL) divergence between softmax outputs for prompts across temporal references. The leftmost heatmap in Figure 7 illustrates these divergences—prompts referencing the present exhibit the lowest divergence, indicating stable and consistent output probabilities. However, significant divergence is observed between past-present and future-present comparisons, highlighting the model's reliance on different priors when predicting tokens for noncontemporary contexts.

The moderate divergence between past and future outputs suggests that the model differentiates between these temporal categories while leveraging some shared contextual grounding. The distinct KL divergences for non-present prompts indicate a logical-level bias, where the model's probabilistic outputs are sensitive to the temporal context, even when the semantic content of the prompts remains equivalent.

5.4 Format Sensitivity Analysis

Figures 6 and 7 (second to fourth columns) show the model's sensitivity to variations in date formats for each temporal reference. Both embeddings and softmax outputs reveal notable patterns of variability across formats.

Representation-Level Bias The cosine similarity heatmaps in Figure 6 indicate that date formats with standard separators (e.g., `%Y-%m-%d`) yield higher consistency, particularly for present references. Non-standard formats (e.g., `%Y%m%d`, `%d%m%Y`) result in lower similarity, especially for past and future prompts. The future category exhibits the highest variability in embeddings across formats, suggesting that futuristic contexts rely more on consistent input structures. In contrast, embeddings for present references remain robust across formats, likely due to the dominance of contemporary contexts in the training data.

Logical-Level Bias The KL divergence heatmaps in Figure 7 reflect similar trends. Standardised data formats (e.g., `%Y-%m-%d`) produce more stable predictions, while non-standard formats (e.g., `%d%m%Y`) introduce higher variability. This sensitivity manifests most prominently in future references, where the KL divergence values are consistently higher, indicating that the model's predictions have increased uncertainty. In contrast, present references remain relatively stable, reinforcing the model's preference for standardised inputs and contemporary contexts.

The results highlight two fundamental temporal biases in the model. First, representation-level biases reveal that the model encodes temporal contexts with distinct semantic structures, likely shaped by training data distribution. Second, logical-level biases indicate inconsistencies in output probabilities across temporal references, underscoring the challenges of achieving temporal generalisation. Furthermore, the heightened sensitivity to non-standard date formats underscores the importance of input standardisation for ensuring consistent model behaviour in temporal reasoning tasks.

6 Discussion

This study highlights the need for targeted strategies to address temporal biases in large language models (LLMs). A key step is to enhance pre-training datasets to ensure temporal diversity, incorporating historical, contemporary, and futuristic contexts. While resources like Redpajama (Weber et al., 2024) and Dolma (Soldaini et al., 2024) are open source, researchers should develop data focused on temporal reasoning with varied formats and cultural contexts.

Post-training methods, such as Direct Preference Optimization (DPO) (Rafailov et al., 2024), offer a promising avenue for fine-tuning models using curated datasets specifically designed to improve their logical temporal reasoning capabilities (Su et al., 2024b; Tan et al., 2023a). These approaches can help align the models' outputs with human-preferred logical reasoning patterns, addressing specific shortcomings in temporal tasks. Additionally, Retrieval-Augmented Generation (RAG) (Liu et al., 2024) enhances LLMs by integrating external knowledge dynamically during inference, allowing the models to access up-to-date or context-specific temporal information beyond their static training data. Moreover, prompting techniques such as Chain of Thought (CoT) prompting (Wei et al., 2023) enable models to break down complex temporal reasoning tasks into incremental steps, improving interpretability and logical coherence (Liu et al., 2024; Xiong et al., 2024b).

However, while these post-training methods significantly mitigate biases in temporal reasoning and improve model performance, they are not sufficient to completely eliminate inherent biases. Factors such as the limitations of pre-trained embeddings, the static nature of foundational knowledge, and the variability in task-specific datasets mean that biases are likely to persist at some level. Thus, post-training approaches should be viewed as an important step toward reducing biases.

7 Conclusion

Our paper addresses the challenges of temporal biases in large language models (LLMs) and proposes a structured approach to analyse their performance with temporal data. We introduced the DateLogicQA dataset and the Semantic Integrity Metric to evaluate the impact of diverse date formats and contexts on tokenization and reasoning. Our findings highlighted representation-level biases, where temporal contexts are inconsistently encoded, and logical-level biases, evident in varying outputs for similar prompts. We suggest mitigation strategies, such as temporally balanced pretraining datasets, post training and prompting methods.

Limitations

Future Scalability The manual human evaluation approach for temporal reasoning performance analysis was time-consuming and challenging for future scalability. Furthermore, the evaluation technique requires high consensus among evaluators, especially when team size expands. Maintaining the evaluation quality in a larger team is also particularly difficult, and it might require more effort to cross-validate the results.

Ethical Considerations

AI usage. It's pertinent to acknowledge the role of AI tools such as ChatGPT in our project. Specifically, Grammarly was utilized minimally and primarily for grammar corrections in our documents. This use was strictly confined to enhancing linguistic accuracy and improving the readability of our written materials. It's important to clarify that the core research, analysis, and development were conducted independently by our team.

Human Annotation. The human annotators involved in this project are professionals with expertise in computer science. No sensitive or personally identifiable data was used in the annotation process, adhering to ethical guidelines and data privacy standards. The human annotators are co authors on this paper.

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A Appendix

B Contributions

Format	Model	Date	Year	Time Period	Century	TC	Tokenized Output	SI	SC	PS
MMDDYYYY	Baseline	10271606	1606	Historical (Pre-2000)	17th Century	3	10 27 1606	1.00	false	true
MMDDYYYY	OLMoE	10271606	1606	Historical (Pre-2000)	17th Century	4	10 27 16 06	0.66	true	true
MMDDYYYY	OLMo	10271606	1606	Historical (Pre-2000)	17th Century	4	10 27 16 06	0.66	true	true
MMDDYYYY	Llama 3	10271606	1606	Historical (Pre-2000)	17th Century	3	102 716 06	0.60	true	true
MMDDYYYY	Llama 3.1	10271606	1606	Historical (Pre-2000)	17th Century	3	102 716 06	0.60	true	true
MMDDYYYY	Llama 3.2	10271606	1606	Historical (Pre-2000)	17th Century	3	102 716 06	0.60	true	true
MMDDYYYY	Davinci-003	10271606	1606	Historical (Pre-2000)	17th Century	3	1027 16 06	0.60	true	true
MMDDYYYY	GPT-3.5	10271606	1606	Historical (Pre-2000)	17th Century	3	102 716 06	0.60	true	true
MMDDYYYY	GPT-4o	10271606	1606	Historical (Pre-2000)	17th Century	3	102 716 06	0.60	true	true
MMDDYYYY	GPT-4	10271606	1606	Historical (Pre-2000)	17th Century	3	102 716 06	0.60	true	true
MMDDYYYY	Cohere Aya	10271606	1606	Historical (Pre-2000)	17th Century	8	1 0 2 7 1 6 0 6	0.45	true	true
MMDDYYYY	Gemma	10271606	1606	Historical (Pre-2000)	17th Century	8	1 0 2 7 1 6 0 6	0.45	true	true
MMDDYYYY	DeepSeek	10271606	1606	Historical (Pre-2000)	17th Century	8	1 0 2 7 1 6 0 6	0.45	true	true
MMDDYYYY	Cohere	10271606	1606	Historical (Pre-2000)	17th Century	8	1 0 2 7 1 6 0 6	0.45	true	true
MMDDYYYY	Qwen	10271606	1606	Historical (Pre-2000)	17th Century	8	1 0 2 7 1 6 0 6	0.45	true	true
MMDDYYYY	Phi 3.5	10271606	1606	Historical (Pre-2000)	17th Century	9	_ 1 0 2 7 1 6 0 6	0.40	true	true
MMDDYYYY	Llama 2	10271606	1606	Historical (Pre-2000)	17th Century	9	_ 1 0 2 7 1 6 0 6	0.40	true	true
MMDDYYYY	Mistral	10271606	1606	Historical (Pre-2000)	17th Century	9	_ 1 0 2 7 1 6 0 6	0.40	true	true
MMDDYYYY	Llama 1	10271606	1606	Historical (Pre-2000)	17th Century	9	_ 1 0 2 7 1 6 0 6	0.40	true	true

Table 4: Generated by Spread-LaTeX

Type of Q	Question	Answer	Date Format	Llama3-70B	Qwen2.5-72B	GPT-4o	GPT-4-turbo	CMDR+
Factual	Which of the following famous people died on 23041616? Answer only with A, B, C, or D: A) Shah Jahan B) Miguel de Cervantes C) Princess Diana D) William Shakespeare	William Shakespeare **OR** Miguel de Cervantes	DDMMYYYY	B) Miguel de Cervantes and D) William Shakespeare	B, D	B) Miguel de Cervantes	D)William Shakespeare	A
Conceptual	The Eiffel Tower was built between 028/1887 to 090/1889. How long did it take to build the Eiffel Tower?	2 years, 2 months, and 3 days	DD/YYYY (Julian)	The Eiffel Tower took 2 years and 1 month to build.	2 years, 10 months, 2 days.	2 years and 1 month.	It took 2 years and 2 months to build.	Construction of the Eiffel Tower took about two years and two months.
Common Sense	A new electric car model is set to be released on 273/2040. Pre-orders open 6 months earlier. On what date can customers start preordering?	On March 30, 2040	DD/YYYY (Julian)	273/2040 - 6 months = 93/2039. Customers can start preordering on this date.	Pre-orders open on 273/2039.	Customers can start pre-ordering on March 273/2039.	Customers can start preordering on March 273, 2040.	The pre-order date is July 273, 2039.
Numerical	What is the time 7 years and 9 months after 10271446?	July 27, 1454	MMDDYYYY	October 27, 2040.	10271446 + 7 years 9 months = 10353406	October 2023 plus 7 years and 9 months is July 2031.	Time: 10429846 (Unix timestamp format).	10279141

Table 5: Model Performance on DateLogicQA

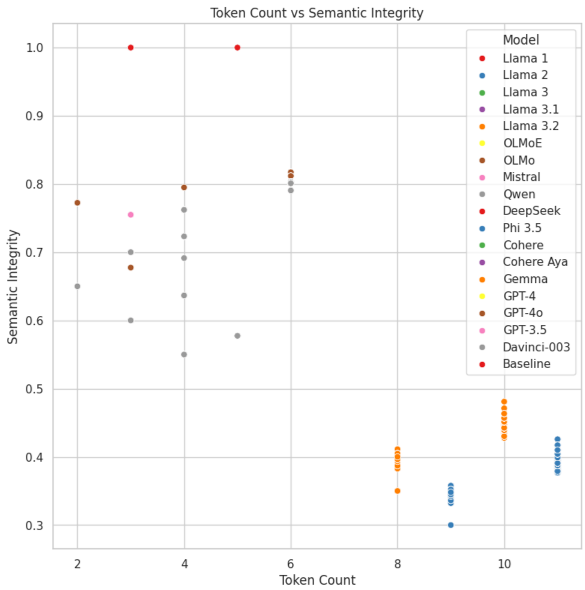

Figure 8: Correlation plot between semantic integrity score against token count

Sections	Contributors
1 - Introduction	All
2 - Related Works	All
3 - DateLogicQA	Cristina & Madiha
4.1 - Semantic Integrity	Tang
4.2 - Human-Led Temporal Bias Assessment	Madiha
4.3 - Understanding Temporal Bias	Gagan
5.1 - Impact of Tokenizers	Tang
5.2 - Temporal Reasoning Analysis	Cristina
5.3 - Temporal Sensitivity Analysis	Gagan
6 - Discussion	All
7 - Conclusion	All
Editing Document	All

Figure 9: Contributions Chart