Language in the Flow of Time: Time-Series-Paired Texts Weaved into a Unified Temporal Narrative

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Abstract

While many advances in time series models focus exclusively on numerical data, research on multimodal time series, particularly those involving contextual textual information, remains in its infancy. With recent progress in large language models and time series learning, we revisit the integration of paired texts with time series through the *Platonic Representation Hypothesis* (Huh et al., 2024), which posits that representations of different modalities converge to shared spaces. In this context, we identify that time-series-paired texts may naturally exhibit periodic properties that closely mirror those of the original time series. Building on this insight, we propose a novel framework, Texts as Time Series (TaTS), which considers the time-series-paired texts to be auxiliary variables of the time series. TaTS can be plugged into *any* existing numerical-only time series models and effectively enable them to handle time series data with paired texts. Through extensive experiments on both multimodal time series forecasting and imputation tasks across benchmark datasets with various existing time series models, we demonstrate that TaTS can enhance multimodal predictive performance without modifying model architectures. Our Code is available at `https://github.com/iDEA-iSAIL-Lab-UIUC/TaTS`.

1 Introduction

Time series modeling plays an important role in a wide range of real-world applications, including finance (Sezer et al., 2020), healthcare (Zhang et al., 2024b), climate (Fu et al., 2024), and energy systems (Kotzur et al., 2017; Li et al., 2015). While extensive research has focused on approaches that rely solely on the numerical values of time series (Zhou et al., 2021; Liu et al., 2024c; Wu et al., 2023b; Wang et al., 2024c), real-world scenarios often involve additional modalities that co-occur with the time series and can provide valuable complementary information (De Baets & Harvey, 2023; Rai et al., 2023; Kyei & Antwi, 2017; Wang et al., 2024d).

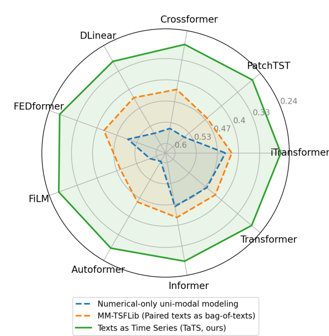


Figure 1: Mean Square Error of modeling frameworks of time series with paired texts. Full results in Appendix E.2.

In scenarios like pandemic policymaking, economic planning, or investment strategies, textual information can provide explanations, updates, or external factors that influence the underlying numerical patterns. However, research on effectively leveraging data from other modalities paired with time series remains in its early stages. In this work, we focus on **time-series paired with texts at each timestamp**, a common data format where textual descriptions are associated with time series at each timestamp in a parallel manner, as illustrated in Figure 3 (left). For instance, during a pandemic, infection rates are often accompanied by government announcements and news reports in real-time (Cinelli et al., 2020). On the one hand, numerical-only models overlook valuable contextual information that may influence or explain the patterns in the time series. On the other hand, the current state-of-the-art approach (Liu et al., 2024a) disregards the unique positional characteristics that time-series-paired texts may inherently possess. Such limitations raise a pivotal question:

What unique attributes may characterize time-series-paired texts, and how can they be systematically integrated to improve time series modeling and predictions?

In this paper, motivated by the *Platonic Representation Hypothesis (PRH)* (Huh et al., 2024), we pioneer the exploration of effectively leveraging paired texts to enrich time series analysis. We identify an intriguing phenomenon, which we term **"Chronological Textual Resonance"** (CTR): depending on data quality, time-series-paired texts may exhibit periodic patterns that closely reflect the temporal dynamics of their corresponding numerical time series. More specifically, despite variations in expressions, the hidden representations of two periodicity-lagged texts associated with time series may demonstrate high similarities, revealing a deeper alignment between textual and numerical modalities. We attribute this phenomenon to the fact that the paired texts inherently evolve in response to the dynamics of the time series itself. Further, we introduce **TT-Wasserstein**, a new metric designed to measure the level of CTR and quantify alignment quality.

Building on these insights, we propose **Texts as Time Series** (TaTS), a simple yet effective framework for integrating paired texts to enhance multimodal time series modeling. Previous studies have shown that different variables in one multivariate time series exhibit similar periodicity properties (Zhang & Yan, 2023; Wang et al., 2024d; Yi et al., 2024), and CTR suggests that time-series-paired texts follow a similar pattern. This observation implies that **paired texts can be considered as special auxiliary variables to augment the original time series**. Motivated by this, TaTS first transforms the paired textual information into a lower-dimensional representation, then combines the original time series with the textual representations as new variables to form an augmented time series. This augmented time series is subsequently fed into existing time series models, allowing them to capture both numerical and textual dynamics. TaTS offers two key benefits: (i) it effectively captures the evolving positional characteristics of texts paired with a time series; and (ii) it functions as a plug-in module, maintaining compatibility with existing time series models. Empirically, the proposed TaTS achieves state-of-the-art performance on both forecasting and imputation tasks. Notably, we observe that a higher CTR level (i.e., a lower TT-Wasserstein) correlates with greater improvements compared to numerical-only modeling. In summary, our contributions are:

- We revisit multimodal time series with the PRH and uncover a previously overlooked phenomenon, termed *Chronological Textual Resonance (CTR)*, that time-series-paired texts may exhibit periodic patterns closely aligned with their corresponding numerical time series. Further, we propose TT-Wasserstein to quantify the level of CTR and the alignment quality.
- Based on this phenomenon, we propose a plug-and-play multimodal time series forecasting framework, *Texts as Time Series (TaTS)*, which transforms text representations into auxiliary variables, seamlessly integrating them into existing time series models.
- Experiments on diverse benchmark datasets and multiple time series models demonstrate TaTS's superior performance without requiring modifications to model architectures.

2 Preliminary

We use calligraphic letters (e.g., $\mathcal{A}$) for sets and bold capital letters for matrices (e.g., $\mathbf{A}$). For matrix indices, $\mathbf{A}[i, j]$ denotes the entry in the i^{th} row and the j^{th} column. For a vector $\mathbf{v}$, $v[i : j]$ represents the sub-vector sliced from the i^{th} to the j^{th} position, inclusively. $\mathbf{A}[i, :]$ returns the i^{th} row in $\mathbf{A}$ and $\mathbf{A}[: i]$ returns the first i rows of $\mathbf{A}$. In this paper, we focus on both forecasting and imputation.

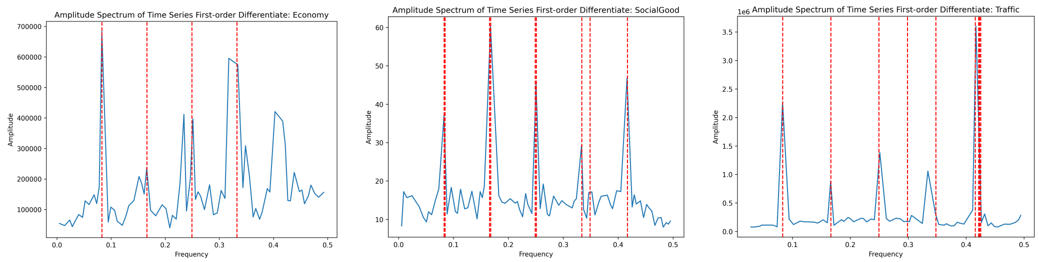
Time Series Forecasting. A time series is denoted as $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\} \in \mathbb{R}^{T\times N}$, where T represents the number of time steps and N denotes the number of variables. $\mathbf{x}_i$ is the time series sequence of the i^{th} variable. When $N > 1$, the time series is referred to as a multivariate time series. Let $\mathbf{X}_{a:b}$ represent the time slice of the series from timestamp a to b, i.e., $\mathbf{X}_{a:b} = \{\mathbf{x}_1[a : b], \mathbf{x}_2[a : b], \ldots, \mathbf{x}_N[a : b]\}$. The task of time series forecasting is to predict the future H steps:

$$\widehat{\mathbf{X}}_{T+1:T+H} = \mathcal{F}\left(\mathbf{X}_{1:T}; \theta_{\text{forecast}}\right) \in \mathbb{R}^{H\times N}, \tag{1}$$

where $\mathcal{F}$ denotes the mapping function, and θ_{forecast} denotes the learnable parameters of $\mathcal{F}$.

Time Series Imputation. The goal of imputation is to estimate missing values in the time series $\mathbf{X}$, where the missing entries are denoted by a binary mask $\mathbf{M} \in \{0, 1\}^{T\times N}$. Specifically, $\mathbf{M}_{t,n} = 1$ indicates $\mathbf{X}_{t,n}$ being observed, $\mathbf{M}_{t,n} = 0$ indicates $\mathbf{X}_{t,n}$ being missing. Formally,

$$\widehat{\mathbf{X}}^{\text{Imputed}} = \mathcal{G}\left(\mathbf{X} \odot \mathbf{M}, \mathbf{M}; \theta_{\text{impute}}\right) \in \mathbb{R}^{T\times N}, \tag{2}$$



(a) Economy (b) Social Good (c) Traffic

Figure 2: By overlaying the top frequencies of paired texts (vertical dashed lines) onto the amplitude spectrum of the time series, it is observed that the time-series-paired texts exhibit similar periodic properties that closely mirror those of the original time series. We term this phenomenon *Chronological Textual Resonance*. More Details are provided in Appendix A.

where $\widehat{\mathbf{X}}^{\text{Imputed}}$ represents the imputed time series, $\mathcal{G}$ denotes the imputation function, θ_{impute} denotes its learnable parameters, and $\odot$ represents the element-wise multiplication. The imputation process aims to recover the missing entries such that $\widehat{\mathbf{X}}^{\text{Imputed}} \approx \mathbf{X}$ with respect to the actual $\mathbf{X}$ values.

Extending Time Series with Paired Texts. In addition to the numerical time series $\mathbf{X} \in \mathbb{R}^{T \times N}$, the dataset $\mathcal{D} = \{\mathbf{X}, \mathbf{S}\}$ includes textual information $\mathbf{S} = \{s_1, s_2, \ldots, s_T\}$, where each s_t represents the text at timestamp t. Each s_t is a string that can be tokenized into a sequence of tokens, i.e., $\text{Tokenize}(s_t) = \{w_{t,1}, w_{t,2}, \ldots, w_{t,L_t}\}$, where L_t denotes the number of tokens in the text at time t. The textual data can be transformed into numerical representations using a textual encoder $\mathcal{H}_{\text{text}}$:

$$\mathbf{e}_t = \mathcal{H}_{\text{text}}(s_t; \theta_{\text{text}}) \in \mathbb{R}^{d_{\text{text}}}, \tag{3}$$

where $\mathbf{e}_t$ is the encoded text representation at time t, d_{text} is text embedding dimension, and θ_{text} are encoder parameters. In this work, we leverage pre-trained large language models to encode the texts.

3 Chronological Textual Resonance (CTR)

The association of time series at each timestamp may imbue time-series-paired texts with unique characteristics that can be effectively harnessed through an appropriate design.

The Platonic Representation Hypothesis. PRH (Huh et al., 2024) posits that different modalities describing the same object converge towards a shared, latent representation. Extending this hypothesis, if time series and paired text both describe the same changing event, their representations are dynamic projections from a common underlying source, and should exhibit similar periodic properties.

To illustrate this hypothesis for time series with paired texts, we analyze three real-world datasets (Liu et al., 2024a), including (i) Economy: The time series represents trade data of the U.S., while the texts describe the general economic conditions of the country. (ii) Social Good: The time series captures the unemployment rate in the U.S., and the texts include detailed unemployment reports. (iii) Traffic: The time series reflects monthly travel volume trends from the U.S. Department of Transportation, with corresponding texts derived from traffic volume reports issued by the same department.

For each dataset $\mathcal{D} = \{\mathbf{X}, \mathbf{S}\}$, we employ Fourier Transform (Nussbaumer, 1982; Sneddon, 1995) to analyze the frequency components of time series data and identify its dominant periodic components, illustrated by the blue curves in Figure 2. To examine the periodicity of texts, we embed each $s_t \in \mathbf{S}$ to obtain the text embedding e_t at timestamp t. Then, we compute their lag-similarity, defined as $d_l = \sum_t \cos(e_t, e_{t+L})$ where L is the lag and $\cos(\cdot, \cdot)$ represents the cosine similarity. If the text embeddings exhibit a significant periodic pattern, the lag-similarity d_l will also fluctuate periodically as the lag l increases (proof in Proposition A.1). Finally, we identify major frequencies (with the largest amplitudes) of the texts by applying FFT to text lag-similarity, and mark them with red dashed lines, as shown in Figure 2. Detailed process is provided in Appendix A. We find that the major frequencies of the paired texts closely match those of the time series. Specifically, the paired texts also show periodicity of 12 (frequency 0.083) for monthly sampled time series, indicating that the paired texts exhibit periodicity that is strongly aligned with the temporal dynamics of the time series.

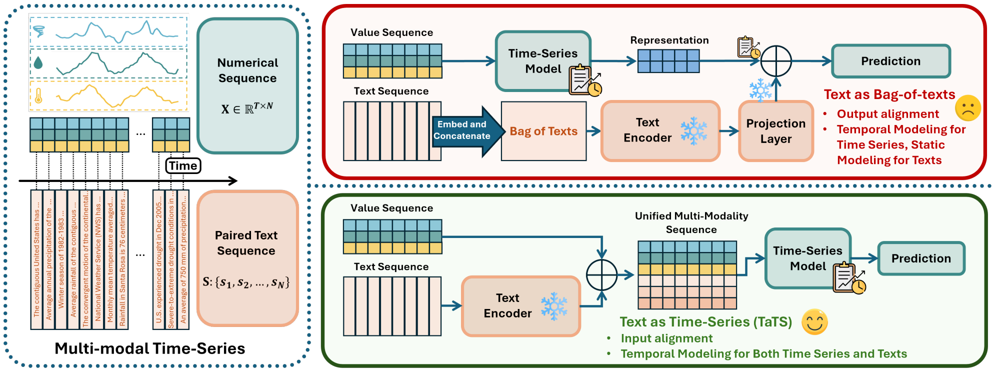


Figure 3: Texts as Time Series (TaTS) framework. As paired texts may exhibit behaviors similar to accompanying variables in a time series, TaTS transforms the paired texts into auxiliary variables. These variables augment the numerical sequence, forming a unified multimodal sequence that can be seamlessly integrated into any existing time series model.

Why may CTR happen? We present three key reasons for the observed alignment in periodicity between time series and their paired texts: (i) **Shared External Drivers**: Both the time series and their paired texts are often influenced by common external factors, such as seasonal changes, recurring events, or societal and economic cycles. These shared drivers naturally induce periodicity in both modalities. (ii) **Influence of Time Series on Texts**: Paired texts often serve as contextual reflections of the underlying time series, adapting and evolving in response to numerical trends. For instance, news articles or government reports accompanying economic indicators are frequently updated in response to the numerical trends. (iii) **Texts Contain Additional Variables with Aligned Periodicity**: Paired texts often include additional variables that are closely related to the time series. For example, if the time series represents economic GDP data, the accompanying texts may reference related variables such as stock market indices or inflation rates. These related variables often exhibit periodicity patterns aligned with the time series and affect the periodicity of the paired texts.

Table 1: TT-Wasserstein measure of Time-MMD (Liu et al., 2024a) datasets and their random shuffle.

Dataset	Monthly Sampled						Weekly Sampled		Daily Sampled
	Agriculture	Climate	Economy	Security	Social Good	Traffic	Energy	Health	Environment
Original	0.026	0.025	0.022	0.049	0.027	0.035	0.307	0.233	0.302
TS shuffled	0.088	0.032	0.098	0.054	0.069	0.102	0.320	0.268	0.358
Text shuffled	0.106	0.037	0.099	0.053	0.072	0.104	0.312	0.277	0.364

Quantifying CTR level. Of course we cannot expect every time series with paired texts at each timestamp to exhibit periodicity similarity. In some cases, texts aligned with timestamps may not provide meaningful or complementary information, for example, daily lottery winning numbers. To this end, we propose a new metric for CTR, TT-Wasserstein, defined as the Wasserstein distance between the normalized spectra of time series and texts. Formally, based on Wasserstein distance $W(P, Q)$ (Kantorovich, 1960), for time series with paired texts dataset $\mathcal{D} = \{\mathbf{X}, \mathbf{S}\}$, after computing normalized frequencies and amplitudes $\tilde{f}_{\text{texts}}, \tilde{f}_{\text{ts}}, \tilde{a}_{\text{texts}}, \tilde{a}_{\text{ts}}$,

$$\begin{aligned}\text{TT-Wasserstein}(\mathcal{D}) = W(P_{\text{texts}}, P_{\text{ts}}) &= \inf_{\gamma \in \Pi(P_{\text{text}}, P_{\text{ts}})} \sum_{i=1}^{n} \sum_{j=1}^{m} \gamma_{ij} \cdot \left| \tilde{f}_{\text{texts}}^{(i)} - \tilde{f}_{\text{ts}}^{(j)} \right| \\ \text{Subject to} \quad \gamma_{ij} \geq 0, \quad & \sum_{j=1}^{m} \gamma_{ij} = \tilde{a}_{\text{texts}}^{(i)}, \quad \sum_{i=1}^{n} \gamma_{ij} = \tilde{a}_{\text{ts}}^{(j)}\end{aligned} \tag{4}$$

Intuitively, TT-Wasserstein$(\mathcal{D})$ quantifies the discrepancy between the spectral distributions of paired texts and time series data. By design, a lower value of TT-Wasserstein$(\mathcal{D})$ should indicate a higher alignment between the textual and numerical modalities. To validate this, we compute our TT-Wasserstein measure of Time-MMD (Liu et al., 2024a) datasets, whose web-retrieved texts are filtered, disentangled, and summarized for relevance and alignment. We also compute TT-Wasserstein on time-series-shuffled or text-shuffled versions of the datasets to disrupt alignment. As shown in Table 1, the corrupted Time-MMD datasets yield much larger Wasserstein distances compared to the original datasets. This finding suggests that TT-Wasserstein can serve as an indicator for the alignment between modalities and a gauge of dataset quality. In Section 5, we will show that TT-Wasserstein can even predict the potential effectiveness of our proposed framework. Additionally, because TT-Wasserstein is an empirical statistical metric, we further analyze its sensitivity and estimation stability in Appendix A.1.

4 Texts as Time Series

An overview of the proposed Texts as Time Series (TaTS) is illustrated in Figure 3.

Concurrent Texts are Secretly Auxiliary Variables. As we elucidated in Section 3, the properties of concurrent texts closely align with those of variables in a multivariate time series: similar to numerical variables, concurrent texts are influenced by shared external drivers and interact dynamically with the time series. Furthermore, mapping concurrent texts to structured variables enables capturing hidden variables embedded within the concurrent texts.

Given the dataset $\mathcal{D} = \{\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\}, \mathbf{S} = \{s_1, s_2, \ldots, s_T\}\}$, TaTS first embed the texts using a text encoder $\mathcal{H}_{\text{text}}$ to obtain text embeddings $\mathbf{E} = \{e_1, e_2, \ldots, e_T\} \in \mathbb{R}^{d_{\text{text}} \times T}$. Since the text embedding dimension d_{text} is typically much larger than the number of variables in the time series, we reduce the dimensionality of the text embeddings by applying a Multi-Layer Perceptron (MLP), mapping them into a lower-dimensional space of reduced dimensionality d_{mapped}.

$$\mathbf{z}_t = \text{MLP}(\mathbf{e}_t; \theta_{\text{MLP}}) \in \mathbb{R}^{d_{\text{mapped}}} \tag{5}$$

Unifying by Plugging-in a Time Series Model. The resulting mapped embeddings $\mathbf{Z} = \{\mathbf{z}_1, \mathbf{z}_2, \ldots, \mathbf{z}_T\} \in \mathbb{R}^{d_{\text{mapped}} \times T}$ are then treated as auxiliary variables in the time series. Specifically, $\mathbf{Z}$ is concatenated with $\mathbf{X}$ to form a unified multimodal sequence:

$$\mathbf{U} = [\mathbf{X}; \mathbf{Z}^{\intercal}]_{\text{dim}=1} \in \mathbb{R}^{T \times (N + d_{\text{mapped}})} \tag{6}$$

The unified sequence $\mathbf{U}$ is then passed into an existing time series model for downstream tasks. Here, we formulate the example of forecasting the next H steps of the time series

$$\widehat{\mathbf{X}}_{T+1:T+H} = \mathcal{F}\left(\mathbf{U}_{1:T}; \theta_{\text{forecast}}\right)[: N] \in \mathbb{R}^{H \times N} \tag{7}$$

where $\mathcal{F}(\cdot; \theta_{\text{forecast}})$ denotes the time series forecasting model with parameters θ_{forecast}, and $[: N]$ extracts the first N variables corresponding to the original time series.

Finally, we joint train the time series model θ_{forecast} as well as the mapping MLP θ_{MLP} using the Mean Squared Error (MSE) loss.

$$\mathcal{L}_{\text{forecast}}(\mathbf{X}, \widehat{\mathbf{X}}) = \frac{1}{H \cdot N} \sum_{t=T+1}^{T+H} \sum_{i=1}^{N} \left(\mathbf{X}_{t,i} - \widehat{\mathbf{X}}_{t,i}\right)^2 \tag{8}$$

where $\mathbf{X}_{t,i}$ and $\widehat{\mathbf{X}}_{t,i}$ represent the ground truth and predicted values of the i^{th} variable at time step t, respectively. TaTS for imputation follows a similar process and is omitted here due to space constraints. Detailed algorithms for both forecasting and imputation are provided in Appendix C.

To conclude this section, we note that while some existing literatures make similar but limited attempts to model covariates in multivariate time series or multiple time series. Our TaTS framework differentiates from those approaches by unifying multi-modality using deep learning architectures. In Section 5, we compare TaTS with these existing approaches.

5 Experiment

In this section, we empirically validate the effectiveness of the proposed TaTS framework. In particular, we use GPT2 (Radford et al., 2019) encoder to embed the paired texts. We also validate the performance of TaTS with other text encoders across different datasets in section 5.2 and Appendix E.7. Implementation details are provided in Appendix D.4.

Table 2: Time-series forecasting performance. Compared to numerical-only unimodal modeling and MM-TSFLib, TaTS consistently and significantly enhances existing time series models to effectively handle paired texts. The results are averaged across all prediction lengths. Full results reported in Appendix E.3. *Promotion* (positive or negative) denotes the percentage reduction (or increase) in MSE or MAE achieved by TaTS compared to the best-performing baseline.

Models		iTransformer (2024c)		PatchTST (2023)		Crossformer (2023)		DLinear (2023)		FEDformer (2022b)		FiLM (2022a)		Autoformer (2021)		Informer (2021)		Transformer (2017)	
Metric		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Agriculture	Uni-modal	0.122	0.251	0.120	0.247	0.323	0.406	0.223	0.354	0.138	0.286	0.139	0.256	0.158	0.297	0.599	0.630	0.354	0.434
	MM-TSFLib	0.112	0.230	0.114	0.233	0.218	0.313	0.218	0.355	0.131	0.275	0.140	0.258	0.158	0.288	0.313	0.414	0.249	0.352
	TaTS (ours)	0.109	0.229	0.114	0.235	0.212	0.312	0.214	0.351	0.131	0.276	0.135	0.251	0.125	0.266	0.255	0.348	0.191	0.313
	Promotion	2.7%	0.4%	0.0%	-0.9%	2.8%	0.3%	1.8%	0.8%	0.0%	-0.4%	2.9%	2.0%	20.9%	7.6%	18.5%	15.9%	23.3%	11.1%
Climate	Uni-modal	1.183	0.871	1.220	0.895	1.124	0.837	1.190	0.872	1.192	0.893	1.270	0.911	1.131	0.865	1.110	0.841	1.092	0.839
	MM-TSFLib	1.044	0.810	1.030	0.806	1.002	0.772	1.104	0.837	1.011	0.797	1.179	0.871	1.053	0.827	1.001	0.792	0.998	0.783
	TaTS (ours)	1.028	0.804	1.004	0.798	0.938	0.755	0.931	0.759	0.926	0.760	0.945	0.772	0.980	0.789	0.930	0.756	0.920	0.753
	Promotion	1.5%	0.7%	2.5%	1.0%	6.4%	2.2%	15.7%	9.3%	8.4%	4.6%	19.8%	11.4%	6.9%	4.6%	7.1%	4.5%	7.8%	3.8%
Economy	Uni-modal	0.014	0.096	0.017	0.105	0.758	0.828	0.058	0.192	0.042	0.166	0.025	0.129	0.071	0.207	1.325	1.110	0.584	0.711
	MM-TSFLib	0.011	0.086	0.014	0.096	0.250	0.458	0.058	0.192	0.035	0.153	0.026	0.129	0.058	0.192	0.432	0.618	0.213	0.416
	TaTS (ours)	0.008	0.077	0.009	0.079	0.219	0.419	0.021	0.117	0.015	0.101	0.009	0.080	0.024	0.121	0.299	0.512	0.079	0.232
	Promotion	27.3%	10.5%	35.7%	17.7%	12.4%	8.5%	63.8%	39.1%	57.1%	34.0%	64.0%	38.0%	58.6%	37.0%	30.8%	17.2%	62.9%	44.2%
Energy	Uni-modal	0.269	0.375	0.269	0.376	0.293	0.406	0.291	0.396	0.240	0.351	0.278	0.385	0.319	0.428	0.309	0.425	0.297	0.405
	MM-TSFLib	0.267	0.378	0.272	0.379	0.291	0.407	0.289	0.395	0.238	0.354	0.279	0.385	0.320	0.428	0.301	0.413	0.293	0.405
	TaTS (ours)	0.265	0.376	0.258	0.371	0.279	0.394	0.283	0.388	0.237	0.355	0.271	0.379	0.314	0.430	0.284	0.396	0.279	0.395
	Promotion	0.7%	-0.3%	4.1%	1.3%	4.1%	3.0%	2.1%	1.8%	0.4%	-1.1%	2.5%	1.6%	1.6%	-0.5%	5.6%	4.1%	4.8%	2.5%
Environment	Uni-modal	0.441	0.494	0.552	0.537	0.551	0.581	0.558	0.591	0.503	0.549	0.577	0.543	0.599	0.598	0.459	0.512	0.460	0.511
	MM-TSFLib	0.421	0.478	0.459	0.501	0.427	0.488	0.429	0.502	0.423	0.486	0.478	0.490	0.452	0.502	0.424	0.480	0.425	0.481
	TaTS (ours)	0.267	0.369	0.273	0.371	0.284	0.403	0.298	0.428	0.275	0.378	0.272	0.371	0.285	0.387	0.285	0.406	0.276	0.397
	Promotion	36.6%	22.8%	40.5%	25.9%	33.5%	17.4%	30.5%	14.7%	35.0%	22.2%	43.1%	24.3%	36.9%	22.9%	32.8%	15.4%	35.1%	17.5%
Health	Uni-modal	1.587	0.817	1.652	0.855	1.535	0.827	1.737	0.848	1.486	0.909	1.982	1.005	1.962	1.039	1.278	0.773	1.378	0.776
	MM-TSFLib	1.446	0.816	1.347	0.797	1.273	0.744	1.541	0.800	1.252	0.792	1.675	0.949	1.494	0.887	1.215	0.740	1.218	0.748
	TaTS (ours)	1.315	0.744	1.283	0.753	1.226	0.728	1.412	0.787	1.244	0.791	1.421	0.838	1.409	0.861	1.183	0.752	1.142	0.718
	Promotion	9.1%	8.8%	4.8%	5.5%	3.7%	2.2%	8.4%	1.6%	0.6%	0.1%	15.2%	11.7%	5.7%	2.9%	2.6%	-1.6%	6.2%	4.0%
Security	Uni-modal	115.94	5.660	112.85	5.371	126.96	6.277	109.11	4.711	114.48	5.158	115.55	5.487	115.27	5.118	131.78	6.623	131.35	6.582
	MM-TSFLib	116.34	5.532	112.84	5.369	125.72	6.183	108.03	4.712	113.73	5.107	109.19	4.897	111.44	4.973	128.95	6.415	128.47	6.378
	TaTS (ours)	112.05	5.151	109.69	5.019	125.16	6.148	107.92	4.676	107.37	4.718	107.85	4.736	108.49	4.787	126.66	6.276	124.58	6.134
	Promotion	3.4%	6.9%	2.8%	6.5%	0.4%	0.6%	0.1%	0.7%	5.6%	7.6%	1.2%	3.3%	2.7%	3.7%	1.8%	2.2%	3.0%	3.8%
Social Good	Uni-modal	1.212	0.483	1.097	0.495	0.865	0.467	1.151	0.712	0.979	0.476	1.261	0.654	1.278	0.701	0.870	0.504	0.910	0.484
	MM-TSFLib	1.197	0.520	1.073	0.515	0.837	0.398	1.083	0.673	0.962	0.462	1.236	0.626	1.229	0.670	0.839	0.457	0.856	0.461
	TaTS (ours)	0.987	0.452	0.972	0.465	0.779	0.412	1.006	0.622	0.888	0.430	1.104	0.626	1.195	0.666	0.810	0.459	0.807	0.419
	Promotion	17.5%	6.4%	9.4%	6.1%	6.9%	-3.5%	7.1%	7.6%	7.7%	6.9%	10.7%	0.0%	2.8%	0.6%	3.5%	-0.4%	5.7%	9.1%
Traffic	Uni-modal	0.213	0.238	0.188	0.242	0.214	0.376	0.230	0.359	0.205	0.264	0.215	0.314	0.212	0.298	0.202	0.355	0.209	0.346
	MM-TSFLib	0.199	0.347	0.178	0.230	0.188	0.334	0.209	0.330	0.193	0.238	0.207	0.300	0.212	0.272	0.172	0.299	0.171	0.295
	TaTS (ours)	0.187	0.217	0.172	0.209	0.168	0.286	0.188	0.300	0.173	0.212	0.176	0.248	0.177	0.229	0.164	0.281	0.164	0.274
	Promotion	6.0%	8.8%	3.4%	9.1%	10.6%	14.4%	10.0%	9.1%	10.4%	10.9%	15.0%	17.3%	16.5%	15.8%	4.7%	6.0%	4.1%	7.1%

Datasets. We evaluate our framework on 18 real-world datasets from Time-MMD (Liu et al., 2024a), FNSPID Dong et al. (2024), and FNF Wang et al. (2024b). The datasets span diverse domains with sample frequencies ranging from daily to weekly and monthly. More details are in Appendix D.1.

Time Series Models and Baselines. To demonstrate the compatibility of TaTS with existing time series models, we integrate TaTS with 9 widely used models across different categories, including (i) Transformer-based models: iTransformer (Liu et al., 2024c), PatchTST (Nie et al., 2023), Crossformer (Zhang & Yan, 2023), Autoformer (Wu et al., 2021), Informer (Zhou et al., 2021) and Transformer (Vaswani et al., 2017). (ii) Linear models: DLinear (Zeng et al., 2023). (iii) Frequency-based models: FEDformer (Zhou et al., 2022b), FiLM (Zhou et al., 2022a).

We compare our TaTS framework with a wide array of baselines, including (a) numerical-only unimodal modeling, which ignores the paired texts and utilizes only the numerical time series with the given time series model; (b) MM-TSFLib (Liu et al., 2024a), a recently library proposed together with Time-MMD datasets for multimodal time series forecasting; (c) covariate-based methods: N-BEATS (Oreshkin et al., 2020), N-HiTS (Challu et al., 2022); (d) convolution-based method TCN (Bai et al., 2018); (e) a recent multimodal time series foundation model ChatTime (Wang et al., 2025).

Metrics. We evaluate the performance of multimodal time series modeling using MSE, MAE, RMSE, MAPE, and MSPE. Due to space constraints, we report only the MSE and MAE results in the main paper, while the results for the other metrics are provided in Appendix E.

5.1 Main Results

Improved Forecasting over Uni-modal Modeling and MM-TSFLib. Table 2 presents the performance results for the time series forecasting task on Time-MMD datasets. For each dataset and time series model, we report the average performance across four different prediction lengths, and

Table 4: TaTS compared with several baselines on a variety of datasets. Best results are bolded and second-best results are underlined. Full results in Table 28.

Methods		TaTS (ours) + iTransformer		TaTS (ours) + PatchTST		TaTS (ours) + FiLM		N-BEATS (2020)		N-HiTS (2022)		TCN (2018)		ChatTime (2025)		GPT4MTS (2024)	
Datasets		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Time-MMD: Multimodal Time Series (2024a)	Agriculture	**0.109**	**0.229**	<u>0.114</u>	<u>0.235</u>	0.135	0.251	3.267	1.458	1.852	1.032	4.168	1.797	0.508	0.447	0.327	0.393
	Climate	1.028	0.804	<u>1.004</u>	<u>0.798</u>	**0.945**	**0.772**	1.093	0.861	1.103	0.858	1.098	0.866	1.568	1.019	1.127	0.873
	Economy	**0.008**	**0.077**	<u>0.009</u>	<u>0.079</u>	<u>0.009</u>	0.080	1.010	0.920	0.444	0.584	5.546	2.349	0.049	0.166	0.014	0.096
	Energy	<u>0.265</u>	<u>0.376</u>	**0.258**	**0.371**	0.271	0.379	0.329	0.424	0.372	0.463	0.430	0.512	0.305	0.417	0.269	0.378
	Environment	**0.267**	**0.369**	0.273	<u>0.371</u>	<u>0.272</u>	<u>0.371</u>	0.518	0.573	0.522	0.583	0.854	0.713	0.580	0.594	0.348	0.422
	Health	<u>1.315</u>	**0.744**	**1.283**	<u>0.753</u>	1.421	0.838	1.660	0.938	1.666	0.898	1.938	0.970	1.668	0.909	1.766	0.875
	Security	112.054	5.151	<u>109.693</u>	<u>5.019</u>	**107.850**	**4.736**	130.065	6.618	138.124	6.978	136.596	6.873	133.106	6.887	119.407	5.198
	Social Good	<u>0.987</u>	**0.452**	**0.972**	<u>0.465</u>	1.104	0.626	1.316	0.665	1.272	0.649	1.314	0.961	1.264	0.652	1.414	0.559
	Traffic	0.187	<u>0.217</u>	**0.172**	**0.209**	<u>0.176</u>	0.248	0.347	0.464	0.268	0.382	0.708	0.744	0.363	0.429	0.195	0.246
FNSPID: Company Stock Price (2024)	Delta Airlines (DAL)	<u>0.087</u>	<u>0.197</u>	**0.086**	**0.192**	0.095	0.201	0.286	0.444	0.226	0.379	0.294	0.466	0.098	0.202	0.093	0.201
	IBM (IBM)	<u>0.564</u>	<u>0.501</u>	**0.550**	**0.490**	0.891	0.695	1.105	0.777	1.215	0.806	1.936	1.123	0.602	0.536	0.639	0.525
	JPMorgan (JPM)	**1.693**	**0.970**	<u>1.872</u>	<u>0.990</u>	2.513	1.096	2.419	1.175	3.426	1.232	3.764	1.711	2.037	1.043	2.133	1.122
	NVIDIA (NVDA)	**0.043**	**0.141**	<u>0.048</u>	<u>0.156</u>	0.050	0.174	0.272	0.434	0.122	0.262	0.457	0.574	0.053	0.161	0.054	0.159
	Pfizer (PFE)	**0.326**	**0.416**	<u>0.347</u>	<u>0.422</u>	0.448	0.477	0.676	0.572	0.824	0.663	0.628	0.559	0.408	0.477	0.369	0.439
	Tesla (TSLA)	<u>0.142</u>	<u>0.281</u>	0.158	0.297	**0.110**	**0.244**	0.188	0.332	0.254	0.416	3.476	1.851	0.158	0.300	0.181	0.303
FNF: Forecast with News (2024b)	Bitcoin Price	<u>2.609</u>	<u>1.112</u>	**2.339**	**1.045**	2.775	1.142	141.738	10.355	159.019	10.535	57.826	6.744	3.590	1.344	2.721	1.152
	Web Traffic	**17.744**	<u>2.712</u>	<u>17.964</u>	**2.653**	18.110	2.772	22.233	3.017	23.263	3.011	21.626	2.842	20.748	2.909	19.260	2.827
	Electricity Demand	0.280	0.396	**0.254**	**0.358**	<u>0.266</u>	<u>0.377</u>	0.416	0.496	0.364	0.468	0.516	0.564	0.532	0.566	0.296	0.395

the full results for each prediction length are provided in Appendix E. For datasets with relatively few samples, we perform short-term forecasting with prediction lengths of $\{6, 8, 10, 12\}$. In contrast, for datasets with a larger number of samples, we perform long-term forecasting with prediction lengths of $\{48, 96, 192, 336\}$. From the results, compared to uni-modal modeling or MM-TSFLib, our TaTS consistently achieves the best performance across all datasets. Notably, by plugging in TaTS to various existing time series models, it achieves an average performance improvement of over 5% on 6 out of 9 datasets and delivers a remarkable performance boost of over 30% on the largest dataset, Environment. The results also demonstrate that TaTS is highly compatible with a wide range of existing time series forecasting models, consistently delivering performance improvements across all of them in both long-term forecasting and short-term forecasting tasks. We provide a visualization of the performance boost in Appendix E.2, showcasing the improvements achieved by different time series models on each dataset.

Improved Time Series Imputation. We evaluate the performance of our TaTS framework on the imputation task using the Climate, Economy, and Traffic datasets, each with an imputation length of 24. Though MM-TSFLib only supports forecasting tasks, we extend it to serve as an imputation baseline by applying a similar linear interpolation. We select one representative time series model from each category and present the results in Table 3. The results demonstrate that TaTS consistently enhances the imputation capabilities of existing time series models, achieving improvements of up to 30% compared to baseline methods.

Table 3: Imputation task performance. Full results in Appendix E.4. *Promotion*: percentage reduction by TaTS over the best-performing baseline.

Models		PatchTST (2023)		DLinear (2023)		FiLM (2022a)	
Metric		MSE	MAE	MSE	MAE	MSE	MAE
Climate	Uni-modal	1.111	0.846	0.969	0.801	1.123	0.829
	MM-TSFLib	1.010	0.821	0.963	0.802	1.130	0.833
	TaTS (ours)	0.878	0.720	0.912	0.757	0.820	0.718
	Promotion	13.1%	12.3%	5.3%	5.5%	27.0%	13.4%
Economy	Uni-modal	0.029	0.138	0.057	0.190	0.077	0.209
	MM-TSFLib	0.026	0.137	0.061	0.196	0.075	0.203
	TaTS (ours)	0.017	0.045	0.045	0.171	0.054	0.168
	Promotion	34.6%	67.2%	21.0%	11.2%	28.0%	17.2%
Traffic	Uni-modal	0.210	0.339	0.245	0.417	0.175	0.311
	MM-TSFLib	0.189	0.341	0.179	0.335	0.169	0.288
	TaTS (ours)	0.131	0.248	0.134	0.297	0.137	0.242
	Promotion	30.7%	26.8%	25.1%	11.3%	18.9%	16.0%

From the above results, effectively leveraging the text modality provides significant benefits when paired texts are available, and our TaTS framework achieves notable improvements over baseline methods that disregard positional information in time-series-paired texts.

TaTS Benefits from Better Alignment (i.e., lower TT-Wasserstein). We compute the average forecasting improvement of TaTS compared to numerical-only modeling, as well as the ratio of TT-Wasserstein between original and shuffled Time-MMD datasets. The results, shown in Table 5, reveal that, within the same sampling frequency, lower TT-Wasserstein original-shuffled ratios tend to correlate with larger performance gains from TaTS (except for Climate). In other words, for paired time series and texts that have stronger CTR, i.e., more relevant, our TaTS could improve performance more. Thus, TT-Wasserstein can indicate the usefulness of paired texts and the potential effectiveness of TaTS when text quality and cross-modal alignment are uncertain.

Comparison beyond Uni-modal Modeling and MM-TSFLib. Besides numerical-only time series models and the MM-TSFLib framework, we compare our TaTS with several other baselines on three dataset sources, including Time-MMD (Liu et al., 2024a), FNSPID (Dong et al., 2024), and

Table 5: TaTS Improvements positively correlated with TT-Wasserstein measure of Time-MMD (Liu et al., 2024a) datasets. "Original-Shuffled TT Ratio" means the ratio of TT-Wasserstein on the original dataset to TT-Wasserstein on the shuffled dataset. "TaTS Improvement" means the average improvement of TaTS over uni-modal time series modeling.

Dataset	Monthly Sampled						Weekly Sampled		Daily Sampled
	Agriculture	Climate	Economy	Security	Social Good	Traffic	Energy	Health	Environment
Original-Shuffled TT Ratio (%)	26.8	72.4	22.3	91.5	38.2	34.6	97.1	85.6	83.6
TaTS Improvement (%)	20.70	18.03	64.80	4.05	10.99	16.78	3.62	19.51	36.00

FNF (Wang et al., 2024b). Although N-BEATS, N-HiTS and TCN are not specifically designed for time series with paired texts, we adapt them by feeding both time series and text embeddings to them. We also include several baselines that explicitly incorporate multimodal information.. For ChatTime, we concatenate all paired texts into a single long text and perform zero-shot inference. For GPT4MTS, we convert the datasets we used into their prescribed input format and directly apply their pipeline. The results averaged from multiple prediction lengths are shown in Table 4, with full results in Table 28. The results show that covariate-based and convolution-based models perform comparably or worse than iTransformer, and consistently underperform compared to our TaTS. Although ChatTime achieves competitive results even in a zero-shot setting, highlighting the value of integrating texts when high-quality texts are available, our TaTS outperforms it through supervised learning. We further compare TaTS with several multimodal methods from concurrent preprints that also evaluate on Time-MMD. Using their reported results (Table 12), we find that TaTS elevates standard time-series backbones into highly competitive models, rivaling recent approaches with substantially more complex designs.

5.2 Further Analysis

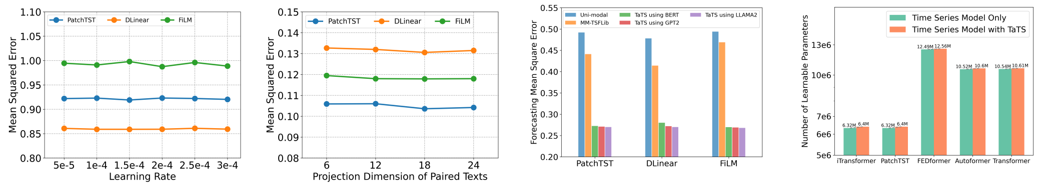
Hyperparameter Sensitivity. We perform hyperparameter studies to evaluate the impact of (i) the learning rate and (ii) d_{mapped}, the dimension to which high-dimensional text embeddings are projected by the MLP, as defined in Equation 5. The results are presented in Figure 4, subfigures (a) and (b), with full results available in Appendix E.5 and Appendix E.6. The findings indicate that TaTS maintains robust performance across different choices of the learning rate and the text projection dimension d_{mapped}.

Ablation with Different Text Encoders in TaTS. While GPT-2 was used as the primary text encoder in our main experiments to demonstrate the effectiveness of TaTS, we further evaluate the performance of TaTS with different text encoders, including BERT (Devlin et al., 2019), GPT-2 (Radford et al., 2019), and LLaMA2 (Touvron et al., 2023). We utilize the official implementations available on Hugging Face and present the results in Figure 4, with full results provided in Appendix E.7. The results show that TaTS remains robust across different text encoders and consistently outperforms both the uni-modal and MM-TSFLib baselines. Notably, as the size of the language models used in TaTS increases from 110M (BERT) to 1.5B (GPT-2) and further to 7B (LLaMA2), we observe a slight improvement in performance. Investigating the relationship between the text encoder size and TaTS's effectiveness remains an open direction for future research.

Ablation with Other Design Choices to Combine Modalities. In our main experiments, TaTS transforms the paired texts into auxiliary variables through embedding, projection and concatenation. Our TaTS framework is readily extensible to other fusion design choices. We evaluate two alternative architectures that replace the MLP projection with: (a) a gated residual and (b) a cross-attention module between the time series and text embeddings. We report the average MSE and MAE across TaTS with iTransformer, PatchTST, and FiLM in Table 6. From the results, these alternative mechanisms achieve similar performance to the MLP-based design. One possible explanation is that linear projections are already highly competitive for time-series representation learning, especially when paired with strong backbone forecasters that account for the majority of the model parameters. We leave the exploration of more fine-grained multimodal fusion designs as an interesting direction for future work.

Table 6: TaTS Ablation on Alternative Modality Fusion Architectures.

Dataset	Climate		Security		Traffic		# Parameters	
TaTS Settings	MSE	MAE	MSE	MAE	MSE	MAE	Fuser	Total
MLP projection (original)	0.992	0.791	109.865	4.968	0.178	0.224	74988	6396658
gated residual	0.998	0.794	110.254	4.965	0.177	0.227	9396	6331066
cross-attention	0.989	0.792	109.729	4.976	0.178	0.221	99340	6421010



(a) (b) (c) (d)

Figure 4: Further analysis of our TaTS framework. (a) Learning rate sensitivity: TaTS maintains stable performance across different learning rates (full results in Appendix E.5). (b) Text Projection Dimension sensitivity: TaTS remains robust across varying d_{mapped} (full results in Appendix E.6). (c) Varying text encoder: TaTS consistently outperforms baselines across different text encoders (full results in Appendix E.7). (d) Efficiency: TaTS introduces only a minor parameter increase ($\sim 1\%$) but significantly improves the performance according to Table 2.

Ablation on Corrupted Datasets. To validate that the performance gains stem from useful textual cues, we conduct corruption experiments where the textual information was randomly shuffled across timestamps. All other settings are unchanged, and the results are in Table 7. When textual alignment is destroyed, the performance drops significantly to matching or even being worse than the uni-modal baseline. This is expected, as randomly shuffled text acts as noise rather than a meaningful signal. Yet our TaTS stays relatively robust because it can learn to assign a small weight to textual information during optimization as a mitigation to noisy texts.

Table 7: TaTS Ablation on text-shuffled datasets.

Dataset	Climate		Security		Traffic	
Settings	MSE	MAE	MSE	MAE	MSE	MAE
iTransformer + TaTS + original data	1.028	0.804	112.05	5.151	0.187	0.217
iTransformer + TaTS + corrupted data	1.242	0.895	117.82	5.767	0.223	0.265
iTransformer + uni-modal + original data	1.183	0.871	115.94	5.660	0.213	0.238

Ablation on Text-Randomly-Dropped Datasets. Similar to corruption ablations, we conduct experiments with randomly dropped texts. Dropped texts are filled with "no information available." The results are in Table 8. While performance degrades slightly as more text is randomly dropped, TaTS remains effective, performing comparably to MM-TSF Lib even with 25% of the text missing. This experiment shows that whenever textual information is available, our TaTS could benefit from it to improve time series modeling.

Table 8: TaTS Ablation on text-dropped datasets.

Dataset	Climate		Security		Traffic	
Settings	MSE	MAE	MSE	MAE	MSE	MAE
TaTS + original data	1.028	0.804	112.05	5.151	0.187	0.217
TaTS + 10% text randomly dropped	1.032	0.809	112.94	5.372	0.194	0.239
TaTS + 25% text randomly dropped	1.056	0.818	114.59	5.231	0.203	0.254

Mitigating Negative Effects of Extremely Noisy Texts. Our ablation on corrupted datasets shows that highly noisy text can cause TaTS to even slightly underperform numerical-only modeling. To address this, we evaluate a simple mitigation strategy: randomly dropping a portion of the noisy texts and replacing them with "no information available." We test drop rates of 40% and 80%. As shown in Table 9, dropping noisy texts allows TaTS to recover performance close to the unimodal baseline, demonstrating the effectiveness of this strategy in handling unreliable text. Practitioners can refer to Appendix B.2 for how TaTS can adapt to scenarios with low-quality texts.

Table 9: Dropping extremely noisy texts mitigates negative effects from them.

Dataset	Climate		Security		Traffic	
Settings	MSE	MAE	MSE	MAE	MSE	MAE
TaTS + corrupted data	1.242	0.895	117.82	5.767	0.223	0.265
TaTS + 60% corrupted data	1.218	0.879	117.43	5.730	0.215	0.260
TaTS + 20% corrupted data	1.201	0.878	116.68	5.713	0.216	0.255
uni-modal + original data	1.183	0.871	115.94	5.660	0.213	0.238

Computational Overhead vs. Performance Gain. We also evaluate the efficiency of our proposed TaTS by measuring the training time per epoch and the total number of model parameters. Figure 4 (d) presents the total number of parameters for the best-performing models in our forecasting experiments. TaTS introduces only a lightweight three-layer MLP to project high-dimensional text embeddings into a lower-dimensional space, adding a minimal number of parameters compared to the original time series models. As a result, the overall parameter count increases by only about 1%.

Due to the inclusion of augmented time series with auxiliary variables from paired texts, the training time per epoch increases slightly, as shown in Figure 5, with average performance of each framework indicated by cross markers. Full results for all datasets are provided in Appendix E.8. Notably, this marginal efficiency trade-off ($\sim 1\%$ in terms of number of learnable parameters and $\sim 8\%$ in terms of training time) leads to significant improvements ($\sim 14\%$) in forecasting performance.

6 Related Work

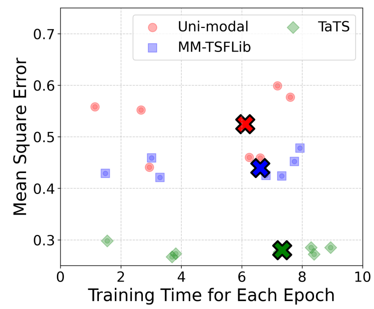


Figure 5: While TaTS incurs a slight increase in training time due to augmented auxiliary variables, it significantly improves forecasting. Full results in Appendix E.8.

Numerical-only Time Series Modeling. Recently, various deep learning models have been developed for time series analysis, which can be broadly categorized into three categories. (1) **Patch-based models.** PatchTST (Nie et al., 2023) segments time series into subseries-level patches to capture dependencies, while Crossformer (Zhang & Yan, 2023) employs a two-stage attention mechanism to model both cross-time and cross-variable dependencies efficiently. Autoformer (Wu et al., 2021) introduces decomposition blocks to separate seasonal and trend-cyclical components. (2) **Global representation models.** iTransformer (Liu et al., 2024c) utilizes attention over global series representations to capture multivariate correlations. Informer (Zhou et al., 2021) reduces self-attention complexity using ProbSparse self-attention for improved efficiency. Dlinear (Zeng et al., 2023) demonstrates that simple linear regression in the raw space can perform competitively on MTS tasks. (3) **Frequency-aware models.** FEDformer (Zhou et al., 2022b) represents series through randomly selected Fourier components, while FiLM (Zhou et al., 2022a) enhances representations with frequency-based layers to reduce noise and accelerate training. In this work, our proposed TaTS is compatible with all of the models listed above.

Time Series with other data sources. In the financial domain, several early works have explored integrating time series with textual data, albeit not in a timestamp-aligned manner, or often leveraging general machine learning models rather than time series-specific architectures. For example, StockNet (Xu & Cohen, 2018) uses a VAE-like model for chaotic stock-text data, while (Rodrigues et al., 2019) fuses time series with a single event-related document. BoEC (Farimani et al., 2021) applies a bag-of-economic-concepts approach, and Dandelion (Zhou et al., 2020) leverages multimodal attention for feature aggregation from multiple text sources. Some works also explored time series with vision information (Liu & Cai, 2012; Gerard et al., 2023; Lütjens et al., 2024) for spatio-temporal analysis. Recently, Time-MMD (Liu et al., 2024a) constructs a dataset of time series paired with parallel text, covering multiple domains, which we used in our main experiments.

Large Language Models on Time Series. The rapid advancement of Large Language Models (LLMs) has inspired a new line of research that transforms time series into natural language representations, enabling LLMs to perform downstream tasks (Zhang et al., 2024c). While these approaches demonstrate strong generalization capabilities due to the power of LLMs (Gruver et al., 2023; Cao et al., 2024; Jin et al., 2024; Xue & Salim, 2024), they also inherit limitations such as hallucination (Huang et al., 2023) and context length constraints (Wang et al., 2024a; Liu et al., 2024b). Notably, a recent work (Tan et al., 2024) suggests that replacing complex LLM architectures with basic attention layers does not necessarily degrade the performance. Another emerging line of work focuses on generating texts from time series, with applications in temporal reasoning and time-series question answering (Chang et al., 2025). MTBench (Chen et al., 2025) provides a comprehensive evaluation framework for assessing whether LLMs can jointly reason over structured numerical trends and unstructured textual narratives. TSAIA (Ye et al., 2025) benchmarks LLMs' multi-step temporal reasoning capabilities. TimeXL (Jiang et al., 2025) further introduces collaborating LLM agents to generate interpretable natural-language explanations alongside time-series forecasts. One notable future direction is to enable latent communications (Zou et al., 2025a;b) between the time series model and language model to build general time series intelligence.

7 Conclusion

Real-world time series data often comes with textual descriptions, yet prior studies have largely overlooked this modality. We identify *Chronological Textual Resonance*, where text embeddings exhibit periodic patterns similar to their paired time series. To leverage this insight, we propose a plug-and-play framework that transforms text representations into auxiliary variables, seamlessly integrating them into existing time series models. Extensive experiments across various forecasting models and real-world datasets demonstrate the state-of-the-art performance of our approach.

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STATEMENTS

ETHICS STATEMENT

Our work is solely focused on the technical challenge of multimodal time series and does not involve any elements that could pose ethical risks.

REPRODUCIBILITY STATEMENT

We provide our full experiment code in the supplementary materials, accompanied by a detailed README to facilitate reproduction. The experimental environment is described in Appendix D, including hardware and software configurations. All benchmark datasets used in this work are publicly available. Comprehensive experiment details, including dataset specifications, hyperparameters, and optimizer settings, are also documented in Appendix D. Reported results are averaged across multiple prediction lengths. Furthermore, Section 5 presents hyperparameter studies, demonstrating the robustness of our proposed TaTS framework.

LARGE LANGUAGE MODEL USAGE STATEMENT

Large Language Models did not play a significant role in research ideation and/or writing to the extent that they could be regarded as a contributor. They were used only for minor refinement of writing and as components within our proposed TaTS framework for handling the text modality.

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Appendix

Roadmap. In this appendix, we provide a detailed overview of our methodology and experimental setup. Appendix A outlines the complete process of frequency analysis for both time series and paired texts. Appendix B discusses of preprints that are related to this work. Appendix C illustrates the TaTS algorithms for time series forecasting and imputation. Appendix D includes details on datasets, hyperparameters, evaluation metrics, and additional implementation specifics. Due to space constraints in the main text, Appendix E presents the full experimental results, including comprehensive forecasting and imputation outcomes, hyperparameter and ablation studies, efficiency evaluations, and visualizations. The table of contents is provided below for reference.

Table of Contents

A Detailed Frequency Analysis Process of Time Series with Paired Texts **19**

A.1 Estimation Stability of TT-Wasserstein . . . 22

B Further Discussion **24**

B.1 Concurrent Works . . . 24

B.2 Limitations . . . 24

B.3 Ethical Impact Statement . . . 25

C Algorithms **26**

C.1 Pseudo Code . . . 26

C.2 Incremental Complexity Introduced by the Text Modality . . . 26

D Experiment Details **28**

D.1 Dataset Statistics and Details . . . 28

D.2 Hyperparameters . . . 29

D.3 Metrics . . . 29

D.4 Implementation Details . . . 30

E Full Experiment Results **32**

E.1 Why should we leverage CTR? . . . 32

E.2 Full Forecasting Performance Comparison Visualization . . . 32

E.3 Full Forecasting Results . . . 32

E.4 Full Imputation Results . . . 44

E.5 Full Hyperparameter Study Results of Learning Rate . . . 45

E.6 Full Hyperparameter Study Results of Text Embedding Dimension . . . 46

E.7 Full Ablation Study Results Using Different Text Encoders . . . 47

E.8 Full Efficiency Results: Computational Overhead vs. Performance Gain Trade-offs 48

A Detailed Frequency Analysis Process of Time Series with Paired Texts

Here, we provide a detailed explanation of the frequency analysis process for both the time series and their paired texts. In Proposition A.1 and A.2, we simplify the proof by analyzing each periodic component individually as a single cosine. This is without loss of generality, as the operations involved are linear. Therefore, the conclusions naturally extend to signals composed of multiple periodic components through linear superposition.

Proposition A.1. *The computation of lag similarity preserves the original periodicities of the data.*

Proof. Let $\mathbf{S} = \{s_t\}_{t=1}^{T}$ represent the paired texts or data sequence, where each s_t corresponds to a time step t. Define the lag similarity at lag k as:

$$\text{LagSim}(k) = \frac{1}{T-k}\sum_{t=1}^{T-k} \text{sim}(s_t, s_{t+k}), \tag{9}$$

where $\text{sim}(\cdot,\cdot)$ is a similarity measure (e.g., cosine similarity).

Now, consider the periodic component of the data sequence $\mathbf{S}$, which can be represented as:

$$s_t = A\cos\left(\frac{2\pi t}{P} + \phi\right), \tag{10}$$

where A is the amplitude, P is the period, and ϕ is the phase.

For two points separated by lag k, the similarity $\text{sim}(s_t, s_{t+k})$ depends on the relative difference between their phases:

$$s_{t+k} = A\cos\left(\frac{2\pi(t+k)}{P} + \phi\right) = A\cos\left(\frac{2\pi t}{P} + \frac{2\pi k}{P} + \phi\right). \tag{11}$$

The lag similarity is then computed as:

$$\text{LagSim}(k) = \frac{1}{T-k}\sum_{t=1}^{T-k} \text{sim}\left(A\cos\left(\frac{2\pi t}{P} + \phi\right), A\cos\left(\frac{2\pi t}{P} + \frac{2\pi k}{P} + \phi\right)\right). \tag{12}$$

Since the cosine function is periodic with period P, the similarity $\text{sim}(s_t, s_{t+k})$ also inherits this periodicity. Therefore, the overall lag similarity $\text{LagSim}(k)$ retains the periodicities of the original sequence $\mathbf{S}$.

Thus, the computation of lag similarity preserves the original periodicities of the data. □

Proposition A.2. *The stabilization of a data sequence using first-order differentiation preserves its original periodicities.*

Proof. Let $\mathbf{S} = \{s_t\}_{t=1}^{T}$ represent a data sequence, where s_t is the value at time step t. The first-order differentiation of the sequence is defined as:

$$\Delta s_t = s_{t+1} - s_t, \quad t = 1, 2, \ldots, T-1. \tag{13}$$

Suppose the sequence $\mathbf{S}$ exhibits periodic behavior with period P and can be represented as:

$$s_t = A\cos\left(\frac{2\pi t}{P} + \phi\right), \tag{14}$$

where A is the amplitude, P is the period, and ϕ is the phase.

The first-order difference of s_t is:

$$\Delta s_t = s_{t+1} - s_t = A\cos\left(\frac{2\pi(t+1)}{P} + \phi\right) - A\cos\left(\frac{2\pi t}{P} + \phi\right). \tag{15}$$

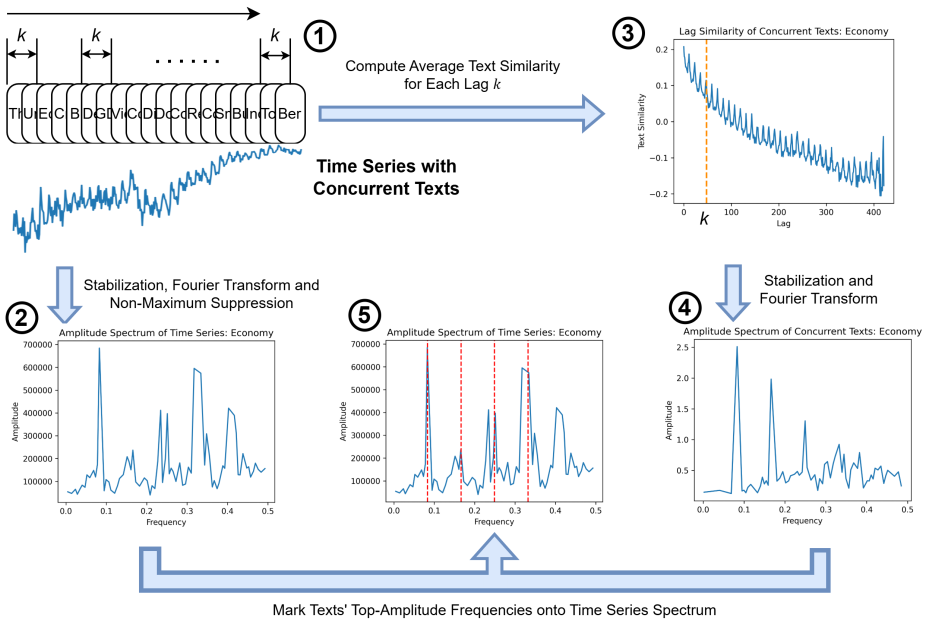


Figure 6: Illustration of the frequency analysis process for time series with paired texts in the Economy dataset. Step ①: Compute the average text similarity for each lag k. Step ②: Stabilize the time series using first-order differentiation, apply Fourier Transform, and perform Non-Maximum Suppression (NMS) to obtain the amplitude spectrum. Step ③: Visualize the lag similarity of paired texts. Step ④: Stabilize the paired texts, compute the Fourier Transform, and visualize the amplitude spectrum. Step ⑤: Overlay the top-l (here l=4) frequencies of paired texts onto the time series amplitude spectrum to highlight shared periodic patterns. All the data transformation operations in this process are periodicity-preserving according to Proposition A.1 and Proposition A.2.

Using the trigonometric identity for the difference of cosines:

$$\cos(x+y) - \cos(x) = -2\sin\left(\frac{y}{2}\right)\sin\left(x + \frac{y}{2}\right), \tag{16}$$

we set $x = \frac{2\pi t}{P} + \phi$ and $y = \frac{2\pi}{P}$, giving:

$$\Delta s_t = -2A\sin\left(\frac{\pi}{P}\right)\sin\left(\frac{2\pi t}{P} + \phi + \frac{\pi}{P}\right). \tag{17}$$

The first term, $\sin\left(\frac{\pi}{P}\right)$, is a constant dependent on the period P. The second term, $\sin\left(\frac{2\pi t}{P} + \phi + \frac{\pi}{P}\right)$, retains the periodicity of P, as it is a sinusoidal function with the same frequency as the original sequence.

Thus, the first-order difference Δs_t preserves the periodicity P of the original data sequence. $\square$

The overall process of frequency analysis for the time series $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\} \in \mathbb{R}^{T\times N}$ and paired texts $\mathbf{S} = \{s_1, s_2, \ldots, s_T\}$ in the Economy dataset $\mathcal{D}_{\text{Economy}} = \{\mathbf{X}, \mathbf{S}\}$ is illustrated in Figure 6. In this process, starting from the original dataset (subfigure ①), the time series and paired texts are analyzed independently. **For the time series $\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\}$, we perform standard frequency analysis**, stabilizing the data through first-order differentiation.

$$\Delta \mathbf{X}_t = \mathbf{X}_{t+1} - \mathbf{X}_t, \quad \text{for } t = 1, 2, \ldots, T-1, \tag{18}$$

where $\Delta \mathbf{X}_t$ represents the first-order difference of the time series. This step removes long-term trends and ensures that the data is stationary, allowing for a more accurate analysis of its frequency components.

Then, we compute the Fourier Transform (Nussbaumer, 1982; Sneddon, 1995) of $\Delta\mathbf{X}$ to analyze its frequency components. The Fourier Transform of $\Delta\mathbf{X}$ is defined as:

$$\mathcal{F}_{\Delta\mathbf{X}}(f) = \sum_{t=1}^{T-1} \Delta\mathbf{X}_t e^{-i2\pi f t}, \tag{19}$$

where f represents the frequency, $\Delta\mathbf{X}_t$ is the first-order difference of the time series at time t, and i is the imaginary unit. The resulting $\mathcal{F}_{\Delta\mathbf{X}}(f)$ provides the amplitude and phase information of each frequency component present in the time series.

The magnitude spectrum, which represents the amplitude of each frequency component, is computed as:

$$|\mathcal{F}_{\Delta\mathbf{X}}(f)| = \sqrt{\text{Re}(\mathcal{F}_{\Delta\mathbf{X}}(f))^2 + \text{Im}(\mathcal{F}_{\Delta\mathbf{X}}(f))^2}, \tag{20}$$

where $\text{Re}(\mathcal{F}_{\Delta\mathbf{X}}(f))$ and $\text{Im}(\mathcal{F}_{\Delta\mathbf{X}}(f))$ are the real and imaginary parts of $\mathcal{F}_{\Delta\mathbf{X}}(f)$, respectively.

By analyzing $|\mathcal{F}_{\Delta\mathbf{X}}(f)|$, we identify the dominant frequencies in the time series, which reveal its periodic patterns. To further highlight the dominant frequencies, we apply Non-Maximum Suppression (NMS) to the magnitude spectrum $|\mathcal{F}_{\Delta\mathbf{X}}(f)|$. NMS ensures that only the most prominent frequencies are retained while suppressing nearby less significant frequencies. The NMS operation is defined as follows:

$$\mathcal{N}(f) = \begin{cases} |\mathcal{F}_{\Delta\mathbf{X}}(f)|, & \text{if } |\mathcal{F}_{\Delta\mathbf{X}}(f)| > |\mathcal{F}_{\Delta\mathbf{X}}(f')| \, \forall f' \in \mathcal{N}(f), \\ 0, & \text{otherwise}, \end{cases} \tag{21}$$

where $\mathcal{N}(f)$ represents a local neighborhood around the frequency f. The operation compares the magnitude of $|\mathcal{F}_{\Delta\mathbf{X}}(f)|$ with those of neighboring frequencies and retains only the largest value within the neighborhood. Frequencies that do not satisfy the condition are set to zero.

After applying NMS, the remaining frequencies represent the dominant periodic components of the time series, making it easier to identify significant periodic patterns. This process eliminates noise and reduces the influence of minor frequency components, enhancing the interpretability of the spectrum. The final visualization of the amplitude spectrum of the time series is shown in Figure 6, subfigure ②.

For the paired texts $\mathbf{S} = \{s_1, s_2, \ldots, s_T\}$, we first embed each s_t using the text encoder $\mathcal{H}_{\text{text}}$:

$$\mathbf{e}_t = \mathcal{H}_{\text{text}}(s_t; \theta_{\text{text}}) \in \mathbb{R}^{d_{\text{text}}}, \tag{22}$$

where θ_{text} represents the parameters of the text encoder, and $\mathbf{e}_t$ is the resulting text embedding at timestamp t.

Since the text embeddings are typically close in the embedding space, leading to similar cosine similarity values, we normalize the embeddings by centering them around their mean to improve numerical stability and enhance sensitivity to differences. Specifically, we compute the mean embedding:

$$\mathbf{e}_{\text{mean}} = \frac{1}{T} \sum_{t=1}^{T} \mathbf{e}_t, \tag{23}$$

and shift all embeddings by subtracting the mean:

$$\mathbf{e}'_t = \mathbf{e}_t - \mathbf{e}_{\text{mean}}, \tag{24}$$

where $\mathbf{e}'_t$ represents the centered (shifted) embeddings.

Next, we compute the average text similarity for each lag $k \in \{1, T-1\}$ as:

$$\text{Sim}(k) = \frac{1}{T-k} \sum_{t=1}^{T-k} \text{sim}(\mathbf{e}'_t, \mathbf{e}'_{t+k}), \tag{25}$$

where $\text{sim}(\mathbf{e}'_t, \mathbf{e}'_{t+k})$ denotes the similarity measure (e.g., cosine similarity) between the centered embeddings at time t and $t+k$, defined as:

$$\text{sim}(\mathbf{e}'_t, \mathbf{e}'_{t+k}) = \frac{\mathbf{e}'_t \cdot \mathbf{e}'_{t+k}}{\|\mathbf{e}'_t\| \|\mathbf{e}'_{t+k}\|}. \tag{26}$$

We visualize the lag similarity of paired texts, $\mathrm{Sim}(k)$, in Figure 6, subfigure ③. Subsequently, we stabilize the data by applying first-order differentiation and perform a Fourier Transform, following a similar process as previously described for the time series frequency analysis. The final visualization of the amplitude spectrum of the paired texts is presented in Figure 6, subfigure ④.

Then, we compute the frequencies with the top-l amplitudes from the lag similarity $\mathrm{Sim}(k)$. We apply the Fourier Transform to $\mathrm{Sim}(k)$:

$$\mathcal{F}_{\text{text}}(f) = \sum_{t=1}^{T-1} \mathrm{Sim}(k)\, e^{-i2\pi f t}, \tag{27}$$

where f is the frequency, and $\mathcal{F}_{\text{text}}(f)$ represents the complex Fourier coefficients corresponding to each frequency f.

Next, we compute the amplitude spectrum as:

$$|\mathcal{F}_{\text{text}}(f)| = \sqrt{\mathrm{Re}(\mathcal{F}_{\text{text}}(f))^2 + \mathrm{Im}(\mathcal{F}_{\text{text}}(f))^2}, \tag{28}$$

where $\mathrm{Re}(\mathcal{F}_{\text{text}}(f))$ and $\mathrm{Im}(\mathcal{F}_{\text{text}}(f))$ are the real and imaginary parts of $\mathcal{F}_{\text{text}}(f)$, respectively.

We then identify the top-l dominant frequencies by selecting the l frequencies corresponding to the largest amplitudes:

$$\mathcal{F}_{\text{top}} = \{f_i \mid |\mathcal{F}_{\text{text}}(f_i)| \text{ is among the top-}l \text{ largest amplitudes}\}. \tag{29}$$

These top-l frequencies represent the most significant periodic components of the paired texts, revealing their dominant temporal patterns. we overlay the top-l (in the Economy dataset l=4) frequencies of the paired texts onto the amplitude spectrum of the time series, as illustrated in Figure 6, subfigure ⑤.

We also visualize the frequency analysis process in the Social Good dataset and Traffic dataset respectively in Figure 7 and Figure 8.

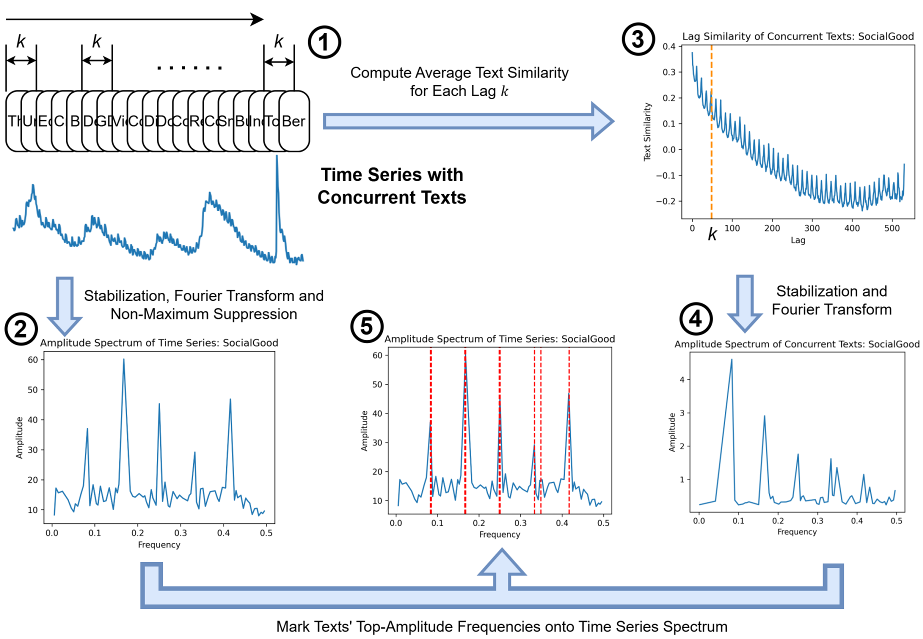


Figure 7: Illustration of the frequency analysis process for time series with paired texts in the Social Good dataset. In Step ⑤, we overlay the top-9 frequencies of paired texts onto the time series amplitude spectrum.

A.1 Estimation Stability of TT-Wasserstein

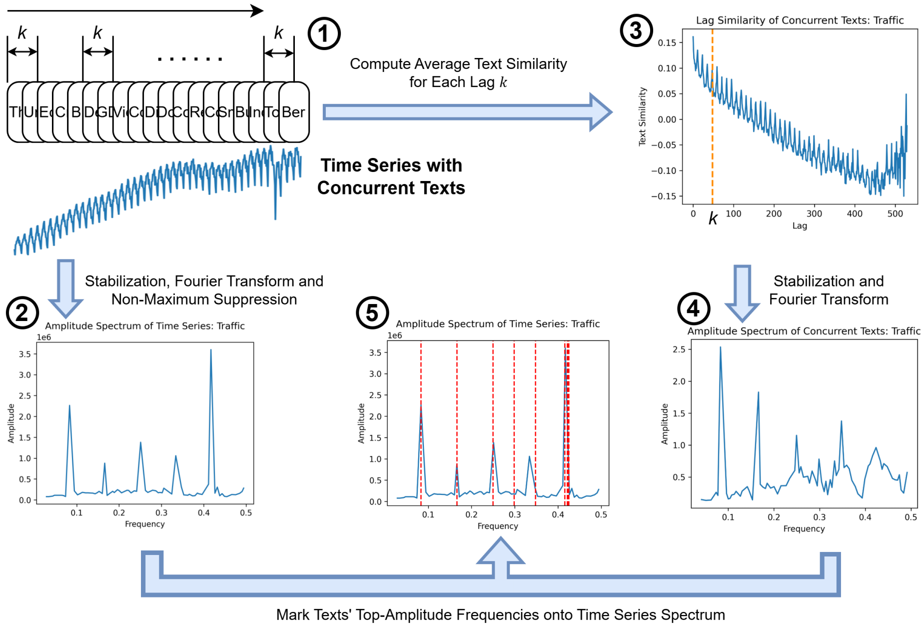


Figure 8: Illustration of the frequency analysis process for time series with paired texts in the Traffic dataset. In Step ⑤, we overlay the top-7 frequencies of paired texts onto the time series amplitude spectrum.

As TT-Wasserstein is an empirically estimated statistical metric, we provide a detailed sensitivity and robustness analysis in this appendix. Our default configuration uses a rectangular window, ℓ_1-normalization of spectral amplitudes, and a frequency grid determined by the full length of the time series (native FFT resolution). To assess the stability of TT-Wasserstein, we perform ablations that vary each of these components: windowing schemes, normalization strategies, and frequency resolutions, while keeping all other settings fixed. The results are summarized in Table 10, where each row reflects the effect of a single deviation from the default configuration. From the results, our TT-Wasserstein is stable across various configuration choices. We also implemented block bootstrap with a bootstrap sample size of 10 for time series and texts to compute the confidence intervals for the default settings in Table 11.

Table 10: TT-Wasserstein measure of Time-MMD (Liu et al., 2024a) datasets. Our TT-Wasserstein is generally stable on different frequency computation configurations.

Dataset	Monthly Sampled Agriculture	Monthly Sampled Climate	Monthly Sampled Economy	Monthly Sampled Security	Monthly Sampled Social Good	Monthly Sampled Traffic	Weekly Sampled Energy	Weekly Sampled Health	Daily Sampled Environment
Default	0.026	0.025	0.022	0.049	0.027	0.035	0.307	0.233	0.302
Hann Window	0.031	0.029	0.016	0.041	0.040	0.057	0.304	0.243	0.306
Hamming Window	0.054	0.025	0.016	0.041	0.037	0.046	0.305	0.242	0.305
Blackman Window	0.061	0.029	0.020	0.036	0.043	0.055	0.297	0.245	0.298
Minmax Normalization	0.032	0.035	0.025	0.043	0.031	0.049	0.345	0.291	0.332
Log Normalization	0.016	0.060	0.046	0.049	0.050	0.048	0.267	0.170	0.286
Zero-padded frequency resolution ($2\times$)	0.046	0.058	0.052	0.051	0.028	0.050	0.280	0.187	0.292
Down-sampled frequency resolution ($\frac{1}{2}\times$)	0.011	0.026	0.039	0.050	0.051	0.025	0.259	0.197	0.298

Table 11: Standard deviation of default TT-Wasserstein measure of Time-MMD (Liu et al., 2024a) datasets by block bootstrap.

Dataset	Monthly Sampled Agriculture	Monthly Sampled Climate	Monthly Sampled Economy	Monthly Sampled Security	Monthly Sampled Social Good	Monthly Sampled Traffic	Weekly Sampled Energy	Weekly Sampled Health	Daily Sampled Environment
Default	±0.06	±0.04	±0.03	±0.03	±0.04	±0.06	±0.21	±0.16	±0.12

B Further Discussion

B.1 Concurrent Works

We discuss concurrent preprints available online that relate to this research, providing a more comprehensive understanding of existing works and ongoing efforts to integrate texts into time series modeling.

(Williams et al., 2024) introduces a benchmark (CiK) for time-series forecasting that integrates both numerical data and textual context. While both (Williams et al., 2024) and our work emphasize the integration of textual context into time series forecasting, the textual contexts in (Williams et al., 2024) are descriptions regarding the time series itself, but in our work, we do not have such a constraint.

(Kim et al., 2024) develops a hybrid forecaster that jointly predicts both time series and textual data by projecting time series to the language space and fine-tuning the pre-trained LLM. Their assumption is that though LLMs are originally for language but not for time series, they can be fine-tuned to adapt to time series.

(Zhang et al., 2024a) introduces a dual-adapter model for time series and textual data, but their data format is similar to (Wang et al., 2025), where the whole time series is paired with one text.

(Xie et al., 2024) proposes a novel multimodal LLM framework (TS-MLLM) that treats time series as a modality akin to images. But they are using synthetic generation and focus on NLP tasks rather than time series forecasting.

Comparison with Concurrent Multimodal Time Series Forecasting Methods. Several concurrent works also explore incorporating multimodal information to enhance time series forecasting and report results on the Time-MMD benchmark (Liu et al., 2024a). TFHTS (Zhou et al., 2025) adopts a dual-tower architecture to fuse time series and textual signals, followed by large language models for forecasting. MCD-TSF (Su et al., 2025a) proposes a multimodal-conditioned diffusion model that adaptively aligns textual context with temporal dynamics. TeR-TSF (Su et al., 2025b) introduces text reinforcement, generating augmented textual descriptions to improve downstream prediction.

For a fair comparison, we follow their evaluation protocol and exclude datasets that exhibit substantial performance gaps, suggesting that their preprocessing pipelines may differ from ours. we report averaged performance over prediction lengths 6, 12, and 18 for monthly-frequency datasets (Agriculture, Climate, Social Good); 12, 24, and 36 for weekly-frequency datasets (Energy, Health); and 48, 96, and 192 for the daily-frequency Environment dataset. Note that, unlike our main experiments, we use a historical window of 36 steps for monthly, 96 for weekly, and 192 for daily datasets. The results are summarized in Table 12. From the results, TaTS achieves the best or second-best performance on 9 out of the 12 metrics. To provide an overall comparison, we compute an average ranking as follows: for each dataset, we assign each method a rank from 1 to 4 for both MSE and MAE (with lower values indicating better performance), average the two ranks to obtain a per-dataset score, and then average these scores across all datasets. Under this ranking scheme, TaTS obtains the smallest average ranking, indicating the best overall performance among concurrent multimodal time series forecasting methods.

B.2 Limitations

This work focuses on revealing and quantifying Chronological Textual Resonance (CTR) and designing the TaTS framework to leverage it. However, several limitations remain. First, we do not thoroughly investigate the data construction processes that may induce CTR, such as biases introduced during text collection or the choice of contextual information. Understanding how these factors affect CTR would provide deeper insights into the robustness and generalizability of our approach. Second, we do not analyze how text embeddings are utilized at the neural level within the TaTS framework. A more detailed study on how the model learns temporal patterns from paired texts could inform improvements in architecture design. Third, the effectiveness of TaTS is influenced by the quality and relevance of paired texts. While we study cases where texts are randomly shuffled, real-world texts could have different patterns, and the model's performance may degrade. Future work could explore methods to assess and enhance text quality or develop more robust models to handle noisy input. Lastly, while TaTS demonstrates strong empirical performance across benchmark datasets,

Table 12: TaTS compared with several concurrent works that have been evaluated on Time-MMD. We use the reported performance in the concurrent works for comparison. Best results are bolded and second-best results are underlined. Full results in Table 28.

Methods		TaTS (Ours) + iTransformer		TFHTS (2025)		MCD-TSF (2025a)		TeR-TSF (2025b)	
Datasets		MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Time-MMD: Multimodal Time Series (2024a)	Agriculture	**0.201**	**0.321**	0.571	0.564	<u>0.222</u>	<u>0.322</u>	0.338	0.402
	Climate	**1.227**	<u>0.890</u>	1.782	0.948	1.583	0.971	<u>1.348</u>	**0.874**
	Energy	0.214	<u>0.321</u>	0.290	0.403	**0.153**	**0.293**	<u>0.202</u>	0.324
	Environment	0.267	0.374	<u>0.262</u>	<u>0.368</u>	0.275	0.379	**0.251**	**0.346**
	Health	**1.372**	<u>0.763</u>	1.514	0.809	1.496	0.811	<u>1.384</u>	**0.756**
	Social Good	<u>1.146</u>	**0.558**	1.352	0.677	**1.035**	<u>0.569</u>	1.199	0.587
Average Ranking		1.83		3.5		2.58		2.08	

its generalization to other types of multimodal time series or domains with fundamentally different patterns remains untested, for example, time series with paired images or audio. We leave these investigations and improvements for future work.

Regarding our third limitation on text quality, we briefly clarify how TaTS may adapt under imperfect textual inputs. When texts are missing at some timestamps, TaTS can simply use a placeholder token (e.g., "no information available"), as validated in our text-random-drop ablations. When temporal alignment is uncertain, small lead–lag shifts mainly affect phase rather than frequency, so TaTS can still leverage the preserved periodic structure. For larger misalignments, standard preprocessing alignment methods may be applied, with TT-Wasserstein serving as a diagnostic to guide how strongly to rely on the text modality.

B.3 Ethical Impact Statement

Our work is solely focused on the technical challenge of multimodal time series and does not involve any elements that could pose ethical risks.

C ALGORITHMS

C.1 PSEUDO CODE

Algorithm 1: Texts as Time Series for Forecasting Task

Input: Time series with concurrent texts embeddings $\mathcal{D} = \{\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\}, \mathbf{E} = \{e_1, e_2, \ldots, e_T\}\}$ in the input training dataset; prediction length H.

Output: TaTS model parameters $\Theta = \{\theta_{\text{forecast}}, \theta_{\text{MLP}}\}$.

Prepare training samples of sequence length L and prediction length H as:

$$\{\mathbf{X}^{(i)} = \mathbf{X}_{l_i+1:l_i+L}, \mathbf{E}^{(i)} = \mathbf{X}_{l_i+1:l_i+L}, \mathbf{Y}^{(i)} = \mathbf{X}_{l_i+L+1:l_i+L+H}\}_{i=1}^{n}$$

Initialize time series model $\mathcal{F}(\cdot; \theta_{\text{forecast}})$; projector $\text{MLP}(\cdot; \theta_{\text{MLP}})$ for dimensionality reduction.

while *not converged* **do**
- **for** *each training sample* $\{\mathbf{X}^{(i)}, \mathbf{E}^{(i)}, \mathbf{Y}^{(i)}\}$ **do**
  - Map $\mathbf{E}^{(i)}$ to $\mathbf{Z}^{(i)}$: $\mathbf{Z}^{(i)}[j] = \text{MLP}(\mathbf{E}^{(i)}[j]; \theta_{\text{MLP}})$
  - Compute $\mathbf{U} = [\mathbf{X}^{(i)}; (\mathbf{Z}^{(i)})^{\intercal}]_{\text{dim=1}}$ as shown in Eq. (6).
  - Forecast: $\widehat{\mathbf{X}}^{(i)} = \mathcal{F}(\mathbf{U}; \theta_{\text{forecast}})[: N]$
  - Optimize: $\arg\min_{\Theta=\{\theta_{\text{forecast}}, \theta_{\text{MLP}}\}} \mathcal{L}_{\text{forecast}}(\mathbf{X}^{(i)}, \widehat{\mathbf{X}}^{(i)})$ as shown in Eq. (8)

return TaTS model parameters $\Theta = \{\theta_{\text{forecast}}, \theta_{\text{MLP}}\}$

Algorithm 2: Texts as Time Series for Imputation Task

Input: Time series with concurrent text embeddings $\mathcal{D} = \{\mathbf{X} = \{\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N\}, \mathbf{E} = \{e_1, e_2, \ldots, e_T\}\}$ in the input training dataset; binary mask $\mathbf{M} \in \{0, 1\}^{T \times N}$.

Output: TaTS model parameters $\Theta = \{\theta_{\text{impute}}, \theta_{\text{MLP}}\}$.

Prepare training samples with observed entries:

$$\{\mathbf{X}^{(i)} = \mathbf{X}_{l_i+1:l_i+L}, \mathbf{E}^{(i)} = \mathbf{E}_{l_i+1:l_i+L}, \mathbf{M}^{(i)} = \mathbf{M}_{l_i+1:l_i+L}\}_{i=1}^{n}$$

Initialize time series imputation model $\mathcal{G}(\cdot; \theta_{\text{impute}})$; projector $\text{MLP}(\cdot; \theta_{\text{MLP}})$ for dimensionality reduction.

while *not converged* **do**
- **for** *each training sample* $\{\mathbf{X}^{(i)}, \mathbf{E}^{(i)}, \mathbf{M}^{(i)}\}$ **do**
  - Map $\mathbf{E}^{(i)}$ to $\mathbf{Z}^{(i)}$: $\mathbf{Z}^{(i)}[j] = \text{MLP}(\mathbf{E}^{(i)}[j]; \theta_{\text{MLP}})$
  - Construct the augmented input: $\mathbf{U} = [(\mathbf{X}^{(i)} \odot \mathbf{M}^{(i)}); (\mathbf{Z}^{(i)})^{\intercal}]_{\text{dim=1}}$
  - Impute missing values: $\widehat{\mathbf{X}}^{\text{Imputed}(i)} = \mathcal{G}(\mathbf{U}; \theta_{\text{impute}})$
  - Optimize: $\arg\min_{\Theta=\{\theta_{\text{impute}}, \theta_{\text{MLP}}\}} \mathcal{L}_{\text{impute}}(\mathbf{X}^{(i)}, \widehat{\mathbf{X}}^{\text{Imputed}(i)})$

return TaTS model parameters $\Theta = \{\theta_{\text{impute}}, \theta_{\text{MLP}}\}$

C.2 INCREMENTAL COMPLEXITY INTRODUCED BY THE TEXT MODALITY

As analyzed in Section 5.2, incorporating textual information introduces some additional computational overhead. This overhead arises from two components: (1) *the cost of encoding the text tokens*, and (2) *the cost of training the forecasting model on the augmented input*. We have empirically evaluated the latter in Section 5.2; here, we provide a theoretical analysis of the former.

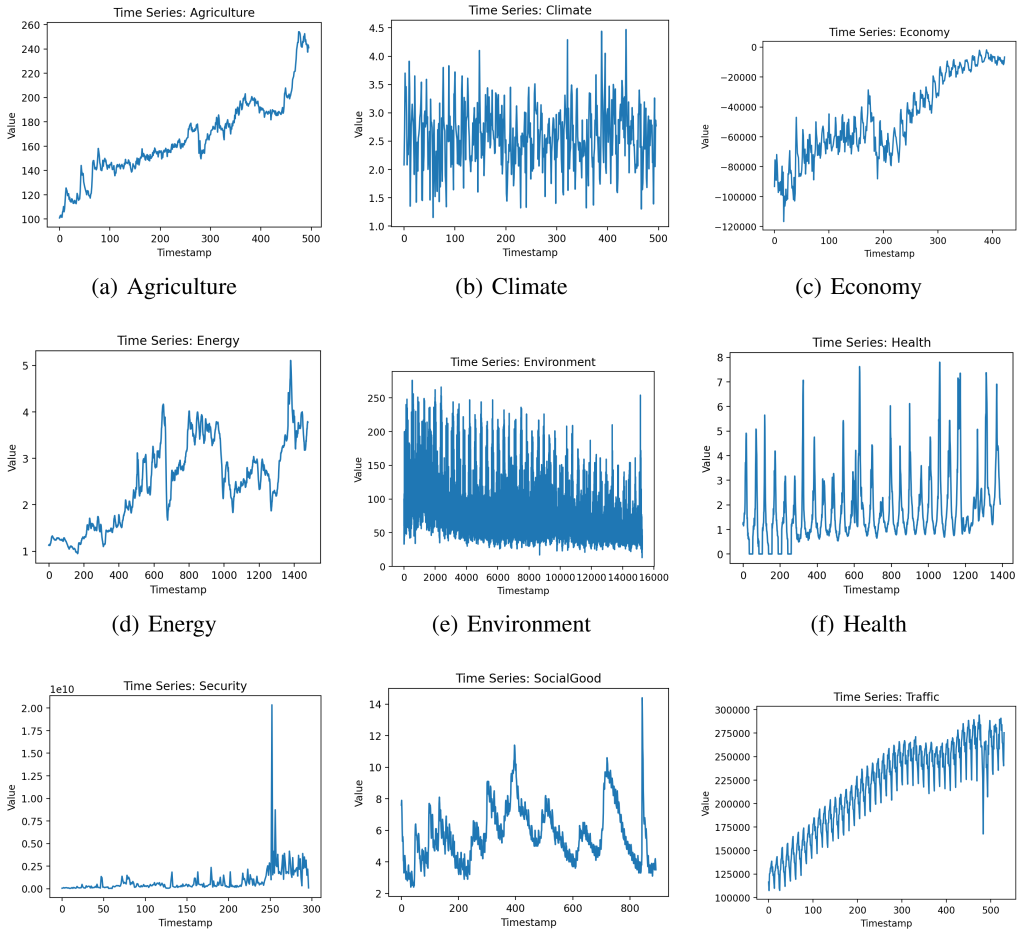
Let the language encoder process each token in time $O(t_{\text{token}})$, and let each timestamp have an associated text description with an average length of l tokens. If the time series contains T timestamps, then the total time complexity for embedding all paired texts is:

$$O(t_{\text{token}} \cdot l \cdot T).$$

This follows because each of the T timestamps requires encoding, on average, l tokens, and each token requires $O(t_{\text{token}})$ time to process. In practice, from our experiments reported in Table 13, this cost is modest for lightweight text encoders (e.g., small Transformers or MLP-based tokenizers), and the embedding step is performed only once per dataset rather than per training iteration. As a result, the added modality introduces only a manageable overhead relative to the overall cost of training modern time-series forecasting models.

Table 13: Wall-clock costs (seconds) to embed texts for Time-MMD (Liu et al., 2024a) datasets.

	Monthly Sampled						Weekly Sampled		Daily Sampled
	Agriculture	Climate	Economy	Security	Social Good	Traffic	Energy	Health	Environment
BERT	0.12	0.21	0.23	0.23	1.7	0.21	0.26	0.46	0.29
GPT-2	0.18	0.25	0.31	0.28	2.5	0.30	0.28	0.55	0.35
LLaMA-2-7B	0.28	0.29	0.37	0.35	10.5	0.40	0.32	0.62	0.42



(a) Agriculture (b) Climate (c) Economy

(d) Energy (e) Environment (f) Health

(g) Security (h) Social Good (i) Traffic

Figure 9: Visualization of the numerical data in each multimodal time series dataset.

D EXPERIMENT DETAILS

D.1 DATASET STATISTICS AND DETAILS

Table 14, Table 15 and Table 16 provide summaries of the statistics for the publicly available real-world datasets. Additionally, we visualize the numerical data for each Time-MMD multimodal time series dataset in Figure 9. For further details, please refer to the original work that introduced these datasets and benchmarks (Liu et al., 2024a).

Table 14: Overview of the numerical data in the Time-MMD datasets (Liu et al., 2024a). "Prediction Length" refers to the number of future time points to be forecasted, with each dataset including four distinct prediction settings. refers to the number of variables (or variates) in each dataset.

Dataset Name/Domain	Prediction Length	Dimension	Frequency	Number of Samples	Timespan
Agriculture	{6, 8, 10, 12}	1	Monthly	496	1983 - Present
Climate	{6, 8, 10, 12}	5	Monthly	496	1983 - Present
Economy	{6, 8, 10, 12}	3	Monthly	423	1989 - Present
Energy	{12, 24, 36, 48}	9	Weekly	1479	1996 - Present
Environment	{48, 96, 192, 336}	4	Daily	11102	1982 - 2023
Health	{12, 24, 36, 48}	11	Weekly	1389	1997 - Present
Security	{6, 8, 10, 12}	1	Monthly	297	1999 - Present
Social Good	{6, 8, 10, 12}	1	Monthly	900	1950 - Present
Traffic	{6, 8, 10, 12}	1	Monthly	531	1980 - Present

Table 15: Overview of the numerical data in the FNSPID (Financial News and Stock Price Integration Dataset) datasets (Dong et al., 2024). "Prediction Length" refers to the number of future time points to be forecasted, with each dataset including four distinct prediction settings. refers to the number of variables (or variates) in each dataset.

Company/Stock Name	Prediction Length	Dimension	Frequency	Number of Samples	Timespan
Delta Airlines (DAL)	{6, 8, 10, 12}	1	Bi-daily	1358	2009 - 2020
IBM (IBM)	{6, 8, 10, 12}	1	Bi-daily	493	2016 - 2020
JPMorgan Chase (JPM)	{6, 8, 10, 12}	1	Bi-daily	565	2018 - 2020
NVIDIA (NVDA)	{6, 8, 10, 12}	1	Bi-daily	1203	2011 - 2020
Pfizer (PFE)	{6, 8, 10, 12}	1	Bi-daily	812	2016 - 2020
Tesla (TSLA)	{6, 8, 10, 12}	1	Bi-daily	294	2019 - 2020

Table 16: Overview of the numerical data in the FNF (From News to Forecast) datasets (Wang et al., 2024b). "Prediction Length" refers to the number of future time points to be forecasted, with each dataset including four distinct prediction settings. refers to the number of variables (or variates) in each dataset.

Dataset Name/Domain	Prediction Length	Dimension	Frequency	Number of Samples	Timespan
Bitcoin Price	{6, 8, 10, 12}	1	Daily	1237	2018 - 2021
Web Traffic	{6, 8, 10, 12}	1	Daily	728	2015 - 2016
Electricity Demand	{6, 8, 10, 12}	1	Daily	1097	2019 - 2021

D.2 Hyperparameters

We use Adam optimizer (Kingma & Ba, 2015) when training the neural networks. The default choices of hyperparameters in our code are provided in Table 17. For LLM-based text encoders, we initialize them using the default configurations provided by Hugging Face[1]. Consistent with existing works (Wu et al., 2023a; Liu et al., 2024c), we apply instance normalization to standardize the time series data within each dataset.

D.3 Metrics

Throughout this paper, we use the following metrics to evaluate performance:

MSE (Mean Squared Error): Measures the average squared difference between the predicted and actual values. It penalizes larger errors more heavily, making it sensitive to outliers.

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2, \tag{30}$$

where y_i and $\hat{y}_i$ denote the ground truth and predicted values, respectively, and n is the number of data points.

MAE (Mean Absolute Error): Represents the average absolute difference between the predicted and actual values, providing a more interpretable measure of average error magnitude.

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|. \tag{31}$$

RMSE (Root Mean Squared Error): The square root of MSE, which provides an error measure in the same units as the original data. It is more sensitive to large deviations than MAE.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}. \tag{32}$$

[1] https://huggingface.co/

Table 17: Default hyperparameters for the TaTS framework

Hyperparameter	Description	Value or Choices
batch_size	The batch size for training	32
criterion	The criterion for calculating loss	Mean Square Error (MSE)
learning_rate	The learning rate for the optimizer	{0.0001, 0.00005, 0.00001}
seq_len	Input sequence length	24
label_len	Start token length for prediction	12
prior_weight	Weight for prior combination	{0, 0.1, 0.2, 0.3, 0.5}
train_epochs	Number of training epochs	50
patience	Early stopping patience	20
text_emb	Dimension of text embeddings	{6, 12, 24}
learning_rate2	Learning rate for MLP layers	{0.005, 0.01, 0.02, 0.05}
pool_type	Pooling type for embeddings	"avg"
init_method	Initialization method for combined weights	"normal"
dropout	dropout	0.1
use_norm	whether to use normalize	True

MAPE (Mean Absolute Percentage Error): Expresses errors as a percentage of the actual values, offering a scale-independent metric that facilitates comparisons across datasets.

$$\text{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \times 100. \tag{33}$$

MSPE (Mean Squared Percentage Error): Similar to MAPE but squares the percentage error, penalizing larger percentage deviations more heavily.

$$\text{MSPE} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{y_i - \hat{y}_i}{y_i}\right)^2. \tag{34}$$

These metrics collectively provide a comprehensive evaluation of model performance, capturing both absolute and relative errors as well as their sensitivity to outliers. For all metrics, **lower values indicate better performance**.

D.4 Implementation Details

D.4.1 Code and Reproducibility

The code for the experiments is included in the supplementary material, accompanied by a comprehensive README file. We provide detailed commands, scripts, and instructions to facilitate running the code. Additionally, the datasets used in the experiments are provided in the supplementary material as CSV files.

D.4.2 Hardware and Environment

We conducted all experiments on an Ubuntu 22.04 machine equipped with an Intel(R) Xeon(R) Gold 6240R CPU @ 2.40GHz, 1.5TB of RAM, and a 32GB NVIDIA V100 GPU. The CUDA version used was 12.4. All algorithms were implemented in Python (version 3.11.11). To run our code, users must install several commonly used libraries, including pandas, scikit-learn, patool, tqdm, sktime, matplotlib, transformers, and others. Detailed installation instructions can be found in the README file within the code directory. We have optimized our code to ensure efficiency. Our tests confirmed that the CPU memory usage remains below 16 GB, while the GPU memory usage is under 20 GB. Additionally, the execution time for a single experiment is less than 10 minutes on our machine.

D.4.3 Data Splitting and Leakage Prevention

To ensure forecasting without access to contemporaneous or future information, we adopt a chronological data-splitting protocol for all datasets. Timestamps are divided into 80% training, 10% validation, and 10% test windows without shuffling. For a forecast at timestamp T, the model receives only time-series values and textual inputs with timestamps $\leq T-1$, while all inputs with timestamps $\geq T$ are masked during prediction.

Timestamp Alignment of Texts. All datasets provide pre-aligned text–time-series pairs by associating each text sample with the timestamp at which it originally became publicly available (e.g., publication or release time). We directly adopt these timestamps, ensuring that the textual inputs available to the model at time $T-1$ correctly reflect real-time accessibility.

Auditing for Retrospective Leakage. Although we do not apply automated filtering procedures, we conduct human audits on random subsets of samples from each dataset to detect retrospective or outcome-summarizing leakage (e.g., texts describing events that occur after the associated timestamp). Across all datasets, we did not observe such leakage. Combined with causal masking, this protocol prevents the models from accessing contemporaneous or future information from either modality.

E FULL EXPERIMENT RESULTS

E.1 WHY SHOULD WE LEVERAGE CTR?

Table 18: Performance on time series forecasting task. Leveraging periodicity with a single-dimension feature can significantly reduce the prediction error.

Method	Economy		Social Good		Traffic	
	MSE(↓)	**MAE(↓)**	**MSE(↓)**	**MAE(↓)**	**MSE(↓)**	**MAE(↓)**
Uniformly Random (+)	5.673	2.356	2.059	1.230	1.207	0.995
Uniformly Random (±)	11.535	2.879	8.860	2.404	3.794	1.618
Normally Random	9.284	2.878	2.926	1.374	3.163	1.511
Exponentially Random	4.521	1.960	3.724	1.564	1.141	0.911
Using 1D Text only	**1.995**	**1.404**	**1.315**	**0.853**	**0.714**	**0.797**

Parallel text provides complementary information and expert knowledge that can significantly enhance the understanding of time series data. To demonstrate the benefits of utilizing periodicity in the text modality, we present an illustrative example in the univariate forecasting task, where the goal is to use $\mathbf{X}_{1:T} = \{\mathbf{x}_1\} \in \mathbb{R}^{T\times 1}$ to predict the next H values, $\widehat{\mathbf{X}}_{T+1:T+H}$. We first concatenate the text embeddings to form $\mathbf{E} = [e_1; e_2; \ldots; e_T]_{\text{dim=1}} \in \mathbb{R}^{d_{\text{text}}\times T}$, then replace $\mathbf{x}_1$ with only the first dimension of the text embeddings to leverage very partial text periodicity, $\mathbf{x}_1' = (\mathbf{E}[1,:])^\intercal \in \mathbb{R}^{T\times 1}$. In other words, we rely solely on a single evolving dimension of the paired text features to forecast future time series values.

As shown in Table 18, leveraging just the periodicity of a single text feature significantly outperforms random time series forecasting. The random baselines mean that the forecasts are purely random according to several different distributions. These random baselines use the training data as well, for example, normally random computes the mean and standard deviation of a normal distribution to forecast the time series. These results highlight that even partial periodicity from the text modality contributes valuable insights for improving forecasting accuracy.

E.2 FULL FORECASTING PERFORMANCE COMPARISON VISUALIZATION

To provide a comprehensive comparison of different frameworks for modeling time series with paired texts, we visualize the forecasting performance using radar plots in Figure E.2. Each subfigure corresponds to a dataset, with each axis representing a different time series model. The axes are inverted, where values closer to the center indicate worse performance, and larger areas signify better results. The results demonstrate that TaTS consistently outperforms both baselines across all datasets while maintaining compatibility with various time series models.

E.3 FULL FORECASTING RESULTS

Due to space limitations, we provide the full results of the time series forecasting task on paired time series and text in the appendix. We conduct extensive experiments across 9 datasets using 9 existing time series models, evaluating various prediction lengths as detailed in Table 14. The complete results are presented from Table 19 to Table 27. Overall, TaTS consistently achieves the best performance across all datasets, time series models, and prediction lengths. The averaged results across all prediction lengths are summarized in the main text (Table 2). For better readability, we also visualize the performance of different frameworks using radar plots, as detailed in Appendix E.2 and Figure 10.

(a) Agriculture (b) Climate (c) Economy

(d) Energy (e) Environment (f) Health

(g) Security (h) Social Good (i) Traffic

Figure 10: Comparison of different frameworks for modeling time series with paired texts. Our TaTS achieves the best performance across all datasets and is compatible with various existing time series models.

Table 19: Full forecasting results for the Agriculture, Climate, and Economy datasets using iTransformer, PatchTST, and Crossformer as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Avg: the average results across all prediction lengths.

Models			iTransformer (2024c)					PatchTST (2023)					Crossformer (2023)				
Method			MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Agriculture	Uni-modal	6	0.077	0.200	0.274	0.090	0.014	0.074	0.197	0.269	0.090	0.014	0.222	0.331	0.412	0.136	0.031
		8	0.104	0.228	0.315	0.100	0.017	0.104	0.234	0.317	0.104	0.018	0.304	0.406	0.496	0.168	0.044
		10	0.142	0.273	0.372	0.119	0.024	0.136	0.262	0.357	0.112	0.021	0.357	0.435	0.530	0.176	0.049
		12	0.167	0.301	0.400	0.128	0.026	0.168	0.294	0.396	0.124	0.025	0.409	0.451	0.582	0.181	0.054
		Avg	0.122	0.251	0.340	0.109	0.020	0.120	0.247	0.335	0.107	0.020	0.323	0.406	0.505	0.165	0.044
	MM-TSFLib	6	0.070	0.189	0.261	0.085	0.013	0.071	0.183	0.261	0.082	0.012	0.146	0.259	0.331	0.106	0.020
		8	0.091	0.212	0.296	0.093	0.016	0.093	0.212	0.296	0.093	0.015	0.171	0.278	0.354	0.112	0.022
		10	0.130	0.248	0.346	0.105	0.019	0.126	0.251	0.344	0.108	0.020	0.252	0.344	0.428	0.136	0.032
		12	0.158	0.272	0.377	0.112	0.022	0.168	0.288	0.391	0.119	0.024	0.304	0.372	0.471	0.144	0.036
		Avg	0.112	0.230	0.320	0.099	0.018	0.114	0.233	0.323	0.100	0.018	0.218	0.313	0.396	0.124	0.027
	TaTS (ours)	6	0.067	0.184	0.256	0.083	0.012	0.066	0.171	0.247	0.076	0.011	0.148	0.264	0.332	0.108	0.020
		8	0.094	0.210	0.297	0.091	0.015	0.096	0.217	0.300	0.094	0.016	0.197	0.298	0.374	0.119	0.026
		10	0.122	0.251	0.341	0.109	0.020	0.126	0.260	0.349	0.113	0.021	0.216	0.315	0.397	0.124	0.028
		12	0.153	0.271	0.374	0.112	0.022	0.166	0.292	0.394	0.123	0.025	0.289	0.371	0.466	0.145	0.036
		Avg	0.109	0.229	0.317	0.099	0.017	0.114	0.235	0.323	0.101	0.018	0.212	0.312	0.392	0.124	0.027
Climate	Uni-modal	6	1.127	0.843	1.052	2.549	50.662	1.259	0.915	1.122	3.168	105.890	1.159	0.852	1.076	3.036	148.840
		8	1.191	0.876	1.088	3.208	134.908	1.208	0.878	1.099	2.778	64.950	1.104	0.829	1.051	2.600	123.988
		10	1.215	0.885	1.100	3.169	123.266	1.218	0.894	1.103	2.746	55.831	1.127	0.829	1.057	3.246	193.108
		12	1.199	0.879	1.091	2.752	65.916	1.197	0.891	1.092	3.177	115.617	1.105	0.837	1.047	3.322	194.844
		Avg	1.183	0.871	1.083	2.920	93.688	1.220	0.895	1.104	2.967	85.572	1.124	0.837	1.058	3.051	165.195
	MM-TSFLib	6	1.031	0.787	1.013	2.298	38.389	1.003	0.800	1.001	2.652	57.709	0.995	0.758	0.996	2.393	51.345
		8	1.039	0.809	1.017	2.598	49.903	1.012	0.790	1.005	2.387	42.258	1.016	0.773	1.007	2.824	107.865
		10	1.049	0.817	1.020	2.547	55.014	1.036	0.813	1.016	2.293	28.894	0.999	0.779	0.997	2.740	95.790
		12	1.057	0.828	1.025	2.894	87.976	1.071	0.822	1.032	2.965	95.248	0.997	0.777	0.994	2.240	43.968
		Avg	1.044	0.810	1.019	2.584	57.821	1.030	0.806	1.014	2.574	56.027	1.002	0.772	0.998	2.549	74.742
	TaTS (ours)	6	1.020	0.797	1.007	2.563	56.209	0.976	0.782	0.987	2.318	33.843	0.924	0.747	0.961	1.895	20.405
		8	1.025	0.797	1.011	2.391	38.756	0.995	0.803	0.997	2.574	57.639	0.923	0.757	0.961	2.318	51.592
		10	1.033	0.808	1.014	2.647	77.697	1.022	0.796	1.007	2.657	76.287	0.963	0.764	0.979	2.439	59.881
		12	1.033	0.812	1.013	2.607	58.107	1.022	0.810	1.009	2.436	42.471	0.943	0.754	0.967	2.220	40.186
		Avg	1.028	0.804	1.011	2.552	57.692	1.004	0.798	1.000	2.496	52.560	0.938	0.755	0.967	2.218	43.016
Economy	Uni-modal	6	0.015	0.099	0.124	0.035	0.002	0.017	0.104	0.129	0.036	0.002	0.659	0.749	0.806	0.257	0.076
		8	0.014	0.098	0.120	0.034	0.002	0.016	0.104	0.128	0.036	0.002	0.661	0.767	0.808	0.263	0.076
		10	0.014	0.094	0.119	0.033	0.002	0.017	0.104	0.130	0.036	0.002	0.836	0.884	0.911	0.303	0.097
		12	0.013	0.091	0.112	0.032	0.002	0.018	0.109	0.135	0.037	0.002	0.875	0.912	0.932	0.313	0.101
		Avg	0.014	0.096	0.119	0.034	0.002	0.017	0.105	0.131	0.036	0.002	0.758	0.828	0.864	0.284	0.087
	MM-TSFLib	6	0.011	0.081	0.103	0.028	0.001	0.014	0.094	0.118	0.033	0.002	0.209	0.420	0.450	0.143	0.024
		8	0.011	0.085	0.106	0.029	0.001	0.015	0.099	0.123	0.034	0.002	0.214	0.424	0.456	0.145	0.024
		10	0.012	0.090	0.110	0.031	0.001	0.013	0.091	0.115	0.031	0.002	0.277	0.463	0.522	0.158	0.032
		12	0.012	0.090	0.110	0.031	0.001	0.016	0.099	0.124	0.034	0.002	0.299	0.526	0.540	0.180	0.034
		Avg	0.011	0.086	0.107	0.030	0.001	0.014	0.096	0.120	0.033	0.002	0.250	0.458	0.492	0.156	0.029
	TaTS (ours)	6	0.008	0.077	0.090	0.027	0.001	0.009	0.080	0.097	0.028	0.001	0.140	0.312	0.367	0.106	0.016
		8	0.008	0.077	0.090	0.027	0.001	0.008	0.078	0.091	0.027	0.001	0.212	0.426	0.454	0.145	0.024
		10	0.009	0.079	0.093	0.027	0.001	0.009	0.079	0.092	0.027	0.001	0.302	0.510	0.544	0.174	0.034
		12	0.008	0.076	0.091	0.026	0.001	0.009	0.080	0.096	0.028	0.001	0.222	0.428	0.466	0.145	0.025
		Avg	0.008	0.077	0.091	0.027	0.001	0.009	0.079	0.094	0.028	0.001	0.219	0.419	0.458	0.142	0.025

Table 20: Full forecasting results for the Energy, Environment, and Health datasets using iTransformer, PatchTST, and Crossformer as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Avg: the average results across all prediction lengths.

Models			iTransformer (2024c)					PatchTST (2023)					Crossformer (2023)				
Method			MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Energy	Uni-modal	12	0.112	0.231	0.305	0.940	10.877	0.105	0.229	0.301	1.120	40.016	0.138	0.262	0.338	1.121	31.808
		24	0.222	0.352	0.438	1.626	35.711	0.241	0.363	0.458	1.507	41.679	0.281	0.399	0.482	1.619	46.008
		36	0.306	0.409	0.511	1.767	58.611	0.304	0.408	0.512	1.782	60.280	0.331	0.443	0.541	3.296	229.673
		48	0.435	0.509	0.617	2.454	95.250	0.427	0.502	0.610	2.405	91.255	0.422	0.521	0.626	4.574	347.533
		Avg	0.269	0.375	0.468	1.697	50.112	0.269	0.376	0.470	1.704	58.307	0.293	0.406	0.497	2.652	163.756
	MM-TSFLib	12	0.107	0.228	0.300	0.999	17.267	0.115	0.242	0.311	1.357	30.739	0.126	0.251	0.326	1.141	30.653
		24	0.223	0.354	0.443	1.692	45.580	0.236	0.361	0.453	1.506	35.353	0.268	0.389	0.477	1.875	69.289
		36	0.313	0.424	0.520	1.916	63.383	0.311	0.413	0.518	1.885	64.280	0.338	0.454	0.553	2.956	202.647
		48	0.423	0.507	0.615	2.494	101.822	0.426	0.501	0.610	2.404	95.489	0.433	0.534	0.637	4.716	415.767
		Avg	0.267	0.378	0.469	1.775	57.013	0.272	0.379	0.473	1.788	56.465	0.291	0.407	0.498	2.672	179.589
	TaTS (ours)	12	0.106	0.234	0.302	1.116	30.716	0.106	0.234	0.300	1.024	17.615	0.127	0.254	0.326	1.053	18.277
		24	0.226	0.355	0.439	1.555	34.060	0.206	0.336	0.417	1.491	35.509	0.253	0.376	0.462	1.823	62.566
		36	0.306	0.411	0.512	1.790	57.729	0.305	0.412	0.506	1.781	57.481	0.312	0.431	0.524	2.602	144.944
		48	0.421	0.502	0.612	2.370	91.346	0.416	0.501	0.607	2.427	93.658	0.425	0.516	0.619	3.314	183.016
		Avg	0.265	0.376	0.466	1.708	53.463	0.258	0.371	0.457	1.681	51.066	0.279	0.394	0.483	2.198	102.201
Environment	Uni-modal	48	0.415	0.473	0.604	2.218	214.087	0.492	0.500	0.644	2.315	238.477	0.495	0.509	0.651	2.275	235.830
		96	0.439	0.493	0.630	2.338	250.510	0.541	0.538	0.693	2.390	256.244	0.562	0.585	0.712	1.880	130.832
		192	0.454	0.506	0.661	2.462	259.311	0.581	0.556	0.741	2.727	356.251	0.567	0.607	0.739	1.659	90.234
		336	0.455	0.505	0.671	2.446	276.348	0.593	0.553	0.763	2.898	424.764	0.582	0.621	0.761	1.656	80.409
		Avg	0.441	0.494	0.641	2.366	250.064	0.552	0.537	0.710	2.583	318.934	0.551	0.581	0.716	1.867	134.326
	MM-TSFLib	48	0.413	0.470	0.600	2.187	211.597	0.441	0.489	0.621	1.954	159.971	0.421	0.472	0.604	1.982	161.068
		96	0.420	0.478	0.616	2.233	213.865	0.461	0.495	0.643	2.063	177.553	0.425	0.485	0.617	1.839	128.131
		192	0.423	0.482	0.636	2.320	225.635	0.462	0.508	0.664	2.203	214.665	0.427	0.495	0.638	1.830	125.150
		336	0.429	0.483	0.651	2.308	236.965	0.472	0.513	0.683	2.210	220.009	0.434	0.500	0.656	1.867	128.536
		Avg	0.421	0.478	0.626	2.262	222.016	0.459	0.501	0.653	2.107	193.049	0.427	0.488	0.629	1.879	135.721
	TaTS (ours)	48	0.268	0.370	0.480	1.140	21.157	0.271	0.377	0.483	1.115	19.355	0.274	0.373	0.485	1.152	20.952
		96	0.267	0.370	0.488	1.123	20.955	0.279	0.376	0.498	1.176	21.868	0.284	0.391	0.505	1.127	18.484
		192	0.272	0.366	0.508	1.215	23.115	0.272	0.366	0.508	1.215	23.342	0.283	0.415	0.523	1.039	14.150
		336	0.261	0.369	0.508	1.174	22.437	0.269	0.366	0.516	1.222	23.081	0.294	0.431	0.541	1.031	12.734
		Avg	0.267	0.369	0.496	1.163	21.916	0.273	0.371	0.501	1.182	21.912	0.284	0.403	0.513	1.087	16.580
Health	Uni-modal	12	1.171	0.674	0.967	2.596	149.272	1.267	0.735	0.999	3.651	262.953	1.453	0.809	1.086	2.699	145.979
		24	1.594	0.807	1.169	2.832	136.133	1.681	0.846	1.167	3.371	160.263	1.537	0.825	1.153	2.744	100.232
		36	1.742	0.862	1.253	2.893	118.496	1.819	0.918	1.281	3.751	243.238	1.565	0.831	1.173	2.687	108.731
		48	1.840	0.923	1.313	3.263	153.559	1.842	0.921	1.310	3.192	152.876	1.586	0.841	1.208	2.730	165.914
		Avg	1.587	0.817	1.175	2.896	139.365	1.652	0.855	1.189	3.491	204.832	1.535	0.827	1.155	2.715	130.214
	MM-TSFLib	12	0.987	0.696	0.928	3.334	190.818	1.029	0.710	0.945	3.400	182.961	1.017	0.664	0.933	2.796	171.177
		24	1.388	0.787	1.113	3.457	169.217	1.288	0.769	1.053	3.207	129.039	1.318	0.747	1.072	2.917	161.566
		36	1.672	0.877	1.216	3.674	176.904	1.460	0.831	1.152	3.492	168.807	1.357	0.775	1.113	3.210	192.422
		48	1.737	0.902	1.270	3.531	155.800	1.612	0.878	1.231	3.317	127.827	1.399	0.788	1.146	2.821	149.248
		Avg	1.446	0.816	1.132	3.499	173.185	1.347	0.797	1.095	3.354	152.159	1.273	0.744	1.066	2.936	168.603
	TaTS (ours)	12	0.939	0.649	0.892	2.764	138.387	0.990	0.659	0.912	2.721	151.988	0.974	0.661	0.911	2.838	163.149
		24	1.251	0.712	1.032	2.744	112.080	1.288	0.764	1.050	3.364	155.937	1.254	0.741	1.062	3.104	170.871
		36	1.489	0.781	1.147	2.885	112.555	1.397	0.780	1.122	2.638	93.114	1.306	0.741	1.083	2.805	152.713
		48	1.581	0.834	1.215	2.909	107.995	1.456	0.808	1.165	2.623	88.216	1.369	0.770	1.136	2.770	144.765
		Avg	1.315	0.744	1.071	2.825	117.754	1.283	0.753	1.062	2.837	122.314	1.226	0.728	1.048	2.879	157.874

Table 21: Full forecasting results for the Security, Social Good, and Traffic datasets using iTransformer, PatchTST, and Crossformer as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Avg: the average results across all prediction lengths.

Models			iTransformer (2024c)					PatchTST (2023)					Crossformer (2023)				
Method			MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Security	Uni-modal	6	113.573	5.698	10.657	6.008	1020.167	108.795	5.119	10.430	4.255	549.239	124.972	6.077	11.179	2.435	113.813
		8	115.878	5.743	10.765	5.977	1035.504	113.534	5.524	10.655	3.681	424.901	126.513	6.237	11.248	1.909	67.155
		10	116.950	5.615	10.814	3.109	332.477	114.820	5.484	10.715	2.523	185.108	127.701	6.346	11.300	1.678	70.642
		12	117.396	5.585	10.835	2.645	262.692	114.253	5.357	10.689	1.951	117.032	128.686	6.449	11.344	1.484	35.512
		Avg	115.949	5.660	10.768	4.435	662.710	112.850	5.371	10.622	3.103	319.070	126.968	6.277	11.268	1.877	71.781
	MM-TSFLib	6	115.170	5.403	10.732	4.284	482.301	109.240	5.189	10.452	4.386	560.668	123.515	5.958	11.114	2.771	175.140
		8	116.158	5.544	10.778	5.742	985.203	113.248	5.445	10.642	3.237	322.665	124.714	6.100	11.168	2.169	126.854
		10	117.340	5.633	10.832	3.090	320.102	114.109	5.442	10.682	2.500	196.618	127.701	6.346	11.300	1.678	70.642
		12	116.694	5.548	10.803	2.560	243.369	114.764	5.398	10.713	2.136	165.771	126.985	6.327	11.269	1.510	42.745
		Avg	116.341	5.532	10.786	3.919	507.744	112.840	5.369	10.622	3.065	311.430	125.729	6.183	11.213	2.032	103.845
	TaTS (ours)	6	107.113	4.856	10.350	3.600	320.907	106.160	4.696	10.303	3.316	282.430	122.887	5.915	11.085	2.831	191.546
		8	112.560	5.204	10.609	3.258	345.121	108.803	5.052	10.431	3.082	312.449	124.302	6.067	11.149	2.656	178.725
		10	113.789	5.227	10.667	2.488	204.306	111.110	5.090	10.541	2.423	205.196	126.203	6.258	11.234	1.720	60.667
		12	114.754	5.318	10.712	2.057	140.148	112.699	5.237	10.616	2.185	171.929	127.263	6.352	11.281	1.433	36.934
		Avg	112.054	5.151	10.584	2.851	252.621	109.693	5.019	10.473	2.752	243.001	125.164	6.148	11.187	2.160	116.968
Social Good	Uni-modal	6	1.129	0.438	0.741	1.395	72.570	1.047	0.443	0.749	1.420	70.855	0.791	0.431	0.681	1.320	39.179
		8	1.133	0.466	0.770	1.448	67.692	1.102	0.458	0.741	1.502	68.611	0.832	0.414	0.668	0.917	13.263
		10	1.275	0.496	0.808	1.718	112.603	1.089	0.469	0.749	1.568	75.225	0.916	0.463	0.728	0.709	6.748
		12	1.313	0.534	0.841	2.052	159.814	1.148	0.610	0.866	2.185	94.833	0.921	0.559	0.766	1.682	54.438
		Avg	1.212	0.483	0.790	1.653	103.170	1.097	0.495	0.776	1.669	77.381	0.865	0.467	0.711	1.157	28.407
	MM-TSFLib	6	1.061	0.451	0.752	1.399	60.240	1.023	0.442	0.741	1.333	62.404	0.753	0.350	0.604	0.753	8.426
		8	1.175	0.498	0.789	1.390	59.283	1.111	0.533	0.807	1.295	34.722	0.814	0.357	0.618	0.576	5.614
		10	1.253	0.561	0.863	1.627	66.938	1.049	0.520	0.799	1.504	54.694	0.866	0.492	0.726	1.127	10.642
		12	1.298	0.570	0.872	1.710	72.310	1.110	0.566	0.840	1.632	50.501	0.917	0.395	0.650	0.693	3.899
		Avg	1.197	0.520	0.819	1.531	64.693	1.073	0.515	0.797	1.441	50.580	0.837	0.398	0.649	0.787	7.145
	TaTS (ours)	6	0.942	0.398	0.677	1.221	49.723	0.923	0.436	0.722	1.153	18.695	0.711	0.407	0.631	0.749	6.772
		8	0.967	0.433	0.713	1.430	50.480	0.900	0.461	0.713	1.279	22.919	0.748	0.453	0.646	0.963	7.987
		10	0.994	0.463	0.740	1.538	54.466	0.996	0.461	0.728	1.348	42.272	0.800	0.373	0.615	0.724	5.977
		12	1.045	0.514	0.780	1.753	61.884	1.069	0.501	0.770	1.549	60.142	0.857	0.415	0.663	0.827	7.195
		Avg	0.987	0.452	0.728	1.486	54.138	0.972	0.465	0.733	1.332	36.007	0.779	0.412	0.639	0.816	6.983
Traffic	Uni-modal	6	0.203	0.228	0.393	0.216	0.307	0.182	0.252	0.377	0.285	0.513	0.227	0.394	0.472	0.340	0.388
		8	0.209	0.236	0.399	0.224	0.321	0.167	0.226	0.348	0.255	0.450	0.216	0.382	0.458	0.324	0.333
		10	0.211	0.243	0.398	0.229	0.321	0.178	0.242	0.362	0.270	0.464	0.202	0.363	0.441	0.313	0.327
		12	0.231	0.246	0.392	0.281	0.532	0.226	0.250	0.393	0.300	0.580	0.212	0.365	0.450	0.337	0.399
		Avg	0.213	0.238	0.395	0.238	0.370	0.188	0.242	0.370	0.278	0.502	0.214	0.376	0.455	0.329	0.362
	MM-TSFLib	6	0.187	0.338	0.422	0.292	0.324	0.165	0.229	0.353	0.248	0.391	0.184	0.335	0.418	0.307	0.371
		8	0.197	0.355	0.433	0.297	0.303	0.163	0.218	0.346	0.237	0.373	0.183	0.331	0.416	0.305	0.367
		10	0.190	0.338	0.422	0.285	0.283	0.174	0.235	0.357	0.252	0.402	0.184	0.331	0.416	0.303	0.363
		12	0.222	0.358	0.459	0.333	0.410	0.211	0.237	0.378	0.281	0.524	0.200	0.340	0.431	0.329	0.427
		Avg	0.199	0.347	0.434	0.302	0.330	0.178	0.230	0.359	0.255	0.422	0.188	0.334	0.420	0.311	0.382
	TaTS (ours)	6	0.174	0.218	0.351	0.227	0.348	0.155	0.204	0.334	0.225	0.359	0.159	0.275	0.372	0.273	0.392
		8	0.177	0.213	0.357	0.215	0.319	0.162	0.210	0.334	0.235	0.389	0.166	0.294	0.385	0.279	0.369
		10	0.186	0.225	0.366	0.223	0.324	0.167	0.214	0.340	0.233	0.368	0.163	0.285	0.378	0.277	0.386
		12	0.213	0.212	0.361	0.241	0.451	0.204	0.209	0.356	0.249	0.468	0.184	0.291	0.395	0.296	0.428
		Avg	0.187	0.217	0.359	0.227	0.361	0.172	0.209	0.341	0.235	0.396	0.168	0.286	0.383	0.281	0.394

Table 22: Full forecasting results for the Agriculture, Climate, and Economy datasets using DLinear, FEDformer, and FiLM as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Avg: the average results across all prediction lengths.

Models			DLinear (2023)					FEDformer (2022b)					FiLM (2022a)				
	Method		MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Agriculture	Uni-modal	6	0.170	0.312	0.395	0.135	0.028	0.091	0.239	0.301	0.110	0.019	0.088	0.207	0.290	0.092	0.015
		8	0.195	0.340	0.423	0.145	0.031	0.127	0.281	0.355	0.127	0.024	0.115	0.230	0.318	0.097	0.017
		10	0.218	0.355	0.448	0.150	0.034	0.154	0.313	0.392	0.142	0.030	0.151	0.255	0.351	0.103	0.020
		12	0.308	0.407	0.514	0.165	0.041	0.180	0.313	0.415	0.134	0.028	0.200	0.333	0.433	0.140	0.030
		Avg	0.223	0.354	0.445	0.149	0.034	0.138	0.286	0.366	0.128	0.025	0.139	0.256	0.348	0.108	0.021
	MM-TSFLib	6	0.166	0.314	0.396	0.137	0.028	0.079	0.219	0.280	0.102	0.016	0.089	0.208	0.291	0.092	0.015
		8	0.193	0.342	0.425	0.148	0.032	0.112	0.269	0.335	0.125	0.024	0.112	0.225	0.314	0.095	0.016
		10	0.214	0.358	0.450	0.153	0.035	0.153	0.292	0.387	0.128	0.026	0.156	0.262	0.357	0.106	0.020
		12	0.300	0.408	0.514	0.167	0.042	0.180	0.319	0.416	0.137	0.028	0.204	0.338	0.437	0.142	0.031
		Avg	0.218	0.355	0.446	0.151	0.034	0.131	0.275	0.354	0.123	0.024	0.140	0.258	0.350	0.109	0.021
	TaTS (ours)	6	0.164	0.311	0.392	0.136	0.028	0.082	0.222	0.286	0.102	0.016	0.087	0.205	0.289	0.091	0.015
		8	0.192	0.343	0.425	0.148	0.032	0.111	0.256	0.330	0.115	0.020	0.110	0.223	0.312	0.094	0.016
		10	0.215	0.358	0.451	0.152	0.035	0.147	0.288	0.377	0.126	0.025	0.146	0.249	0.345	0.100	0.019
		12	0.287	0.392	0.496	0.159	0.038	0.183	0.339	0.418	0.145	0.029	0.196	0.328	0.429	0.138	0.029
		Avg	0.214	0.351	0.441	0.149	0.033	0.131	0.276	0.353	0.122	0.023	0.135	0.251	0.344	0.106	0.020
Climate	Uni-modal	6	1.158	0.866	1.076	3.462	204.312	1.206	0.909	1.098	4.551	394.050	1.277	0.912	1.129	4.953	410.091
		8	1.191	0.874	1.091	3.400	190.434	1.175	0.897	1.084	3.680	176.984	1.158	0.862	1.076	3.282	162.026
		10	1.225	0.882	1.107	3.392	185.912	1.199	0.893	1.095	3.215	134.937	1.160	0.857	1.077	2.152	48.217
		12	1.185	0.868	1.089	2.856	126.200	1.190	0.875	1.091	2.883	99.696	1.487	1.012	1.219	3.993	164.875
		Avg	1.190	0.872	1.091	3.277	176.715	1.192	0.893	1.092	3.582	201.417	1.270	0.911	1.125	3.595	196.302
	MM-TSFLib	6	1.074	0.822	1.036	2.997	154.862	1.012	0.795	1.006	2.492	59.880	1.165	0.869	1.079	3.798	270.733
		8	1.108	0.844	1.053	3.117	160.555	1.003	0.787	1.001	2.265	34.593	1.173	0.867	1.083	3.599	191.009
		10	1.123	0.844	1.059	3.233	167.366	1.011	0.810	1.004	2.133	24.604	1.134	0.843	1.065	1.946	31.959
		12	1.112	0.838	1.054	2.815	116.283	1.019	0.795	1.007	2.321	40.325	1.245	0.904	1.116	3.641	223.644
		Avg	1.104	0.837	1.050	3.040	149.767	1.011	0.797	1.004	2.303	39.851	1.179	0.871	1.086	3.246	179.336
	TaTS (ours)	6	0.905	0.749	0.951	2.025	36.745	0.893	0.748	0.945	1.806	13.948	0.912	0.758	0.955	2.598	82.597
		8	0.926	0.756	0.962	2.018	37.680	0.937	0.771	0.968	1.893	16.622	0.917	0.751	0.957	1.939	26.990
		10	0.943	0.764	0.971	1.989	34.385	0.924	0.751	0.960	1.756	14.796	0.947	0.759	0.972	1.597	10.958
		12	0.950	0.766	0.973	1.938	30.964	0.952	0.770	0.974	1.921	21.544	1.005	0.821	1.003	2.686	68.310
		Avg	0.931	0.759	0.964	1.992	34.944	0.926	0.760	0.962	1.844	16.727	0.945	0.772	0.972	2.205	47.214
Economy	Uni-modal	6	0.056	0.189	0.236	0.065	0.006	0.042	0.168	0.203	0.058	0.005	0.021	0.115	0.146	0.039	0.002
		8	0.056	0.191	0.237	0.066	0.006	0.039	0.162	0.197	0.056	0.005	0.028	0.132	0.168	0.045	0.003
		10	0.047	0.173	0.216	0.060	0.006	0.036	0.153	0.188	0.053	0.004	0.026	0.134	0.162	0.045	0.003
		12	0.075	0.216	0.272	0.074	0.009	0.053	0.183	0.225	0.063	0.006	0.027	0.133	0.163	0.046	0.003
		Avg	0.058	0.192	0.240	0.066	0.007	0.042	0.166	0.203	0.058	0.005	0.025	0.129	0.160	0.044	0.003
	MM-TSFLib	6	0.059	0.200	0.243	0.070	0.007	0.035	0.153	0.188	0.053	0.004	0.018	0.104	0.133	0.036	0.002
		8	0.062	0.194	0.248	0.068	0.007	0.043	0.170	0.206	0.059	0.005	0.031	0.138	0.177	0.047	0.003
		10	0.064	0.195	0.253	0.068	0.008	0.040	0.160	0.200	0.056	0.005	0.026	0.133	0.160	0.045	0.003
		12	0.049	0.180	0.221	0.062	0.006	0.024	0.129	0.157	0.045	0.003	0.029	0.140	0.170	0.048	0.003
		Avg	0.058	0.192	0.241	0.067	0.007	0.035	0.153	0.188	0.053	0.004	0.026	0.129	0.160	0.044	0.003
	TaTS (ours)	6	0.020	0.115	0.141	0.040	0.002	0.012	0.093	0.111	0.033	0.002	0.009	0.080	0.096	0.028	0.001
		8	0.020	0.115	0.142	0.040	0.002	0.014	0.099	0.120	0.034	0.002	0.009	0.079	0.096	0.028	0.001
		10	0.019	0.112	0.137	0.039	0.002	0.016	0.106	0.126	0.037	0.002	0.009	0.079	0.096	0.027	0.001
		12	0.025	0.127	0.157	0.044	0.003	0.017	0.107	0.129	0.037	0.002	0.009	0.081	0.096	0.028	0.001
		Avg	0.021	0.117	0.144	0.041	0.002	0.015	0.101	0.121	0.035	0.002	0.009	0.080	0.096	0.028	0.001

Table 23: Full forecasting results for the Energy, Environment, and Health datasets using DLinear, FEDformer, and FiLM as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Avg: the average results across all prediction lengths.

Models			DLinear (2023)					FEDformer (2022b)					FiLM (2022a)				
	Method		MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Energy	Uni-modal	12	0.136	0.264	0.335	0.947	10.373	0.095	0.212	0.281	0.895	9.380	0.118	0.245	0.314	1.208	25.502
		24	0.261	0.385	0.467	1.453	33.690	0.170	0.303	0.385	1.573	47.676	0.221	0.347	0.433	1.414	29.039
		36	0.335	0.437	0.528	1.780	56.178	0.249	0.373	0.475	2.165	133.305	0.335	0.434	0.533	1.852	60.033
		48	0.431	0.498	0.603	2.294	83.886	0.445	0.514	0.643	4.141	340.071	0.437	0.512	0.620	2.414	89.205
		Avg	0.291	0.396	0.483	1.619	46.032	0.240	0.351	0.446	2.194	132.608	0.278	0.385	0.475	1.722	50.945
	MM-TSFLib	12	0.133	0.262	0.332	0.950	10.725	0.098	0.227	0.289	1.083	15.260	0.119	0.247	0.315	1.202	24.419
		24	0.256	0.380	0.461	1.428	32.596	0.172	0.300	0.388	1.425	47.727	0.224	0.349	0.436	1.415	28.417
		36	0.340	0.442	0.533	1.803	56.982	0.252	0.376	0.477	2.120	124.465	0.332	0.431	0.531	1.839	59.454
		48	0.428	0.496	0.601	2.287	83.443	0.430	0.511	0.611	2.775	146.406	0.440	0.514	0.623	2.416	89.684
		Avg	0.289	0.395	0.482	1.617	45.936	0.238	0.354	0.441	1.851	83.465	0.279	0.385	0.476	1.718	50.493
	TaTS (ours)	12	0.132	0.260	0.330	0.954	11.225	0.090	0.210	0.275	0.880	12.877	0.118	0.245	0.314	1.202	25.174
		24	0.236	0.359	0.441	1.359	29.647	0.172	0.305	0.387	1.375	44.042	0.222	0.347	0.434	1.410	28.640
		36	0.340	0.442	0.533	1.805	57.123	0.250	0.372	0.472	2.412	152.144	0.311	0.414	0.514	1.773	55.535
		48	0.425	0.493	0.597	2.285	84.710	0.435	0.531	0.631	3.501	222.058	0.434	0.510	0.618	2.399	88.602
		Avg	0.283	0.388	0.475	1.601	45.676	0.237	0.355	0.441	2.042	107.780	0.271	0.379	0.470	1.696	49.488
Environment	Uni-modal	48	0.478	0.531	0.646	1.791	119.315	0.505	0.543	0.671	1.932	128.444	0.494	0.502	0.644	2.323	241.494
		96	0.562	0.608	0.724	1.539	68.485	0.465	0.524	0.657	2.440	237.225	0.581	0.546	0.707	2.639	314.062
		192	0.592	0.608	0.748	1.938	132.178	0.510	0.556	0.702	2.656	297.619	0.612	0.559	0.759	3.081	461.654
		336	0.600	0.618	0.768	1.938	134.420	0.531	0.573	0.725	2.528	300.421	0.621	0.566	0.779	2.989	440.819
		Avg	0.558	0.591	0.722	1.801	113.600	0.503	0.549	0.689	2.389	240.927	0.577	0.543	0.722	2.758	364.507
	MM-TSFLib	48	0.414	0.474	0.598	1.888	142.797	0.413	0.468	0.599	1.867	128.047	0.469	0.484	0.652	2.046	177.399
		96	0.420	0.489	0.615	1.743	112.990	0.413	0.479	0.613	1.998	138.883	0.476	0.493	0.662	1.987	173.914
		192	0.439	0.521	0.650	1.659	92.080	0.423	0.489	0.635	2.205	197.315	0.477	0.486	0.674	2.135	218.811
		336	0.444	0.526	0.664	1.680	95.029	0.445	0.507	0.665	1.850	125.600	0.490	0.497	0.696	2.233	243.544
		Avg	0.429	0.502	0.632	1.742	110.724	0.423	0.486	0.628	1.980	147.461	0.478	0.490	0.671	2.100	203.417
	TaTS (ours)	48	0.272	0.385	0.486	1.083	17.610	0.272	0.369	0.484	1.172	21.826	0.269	0.373	0.481	1.124	19.765
		96	0.301	0.427	0.528	1.034	13.731	0.271	0.371	0.495	1.143	22.305	0.279	0.377	0.499	1.180	21.986
		192	0.306	0.443	0.544	1.007	11.494	0.277	0.379	0.501	1.145	22.438	0.271	0.367	0.507	1.202	22.318
		336	0.313	0.456	0.557	0.996	10.408	0.278	0.393	0.524	1.137	18.379	0.267	0.366	0.514	1.210	22.394
		Avg	0.298	0.428	0.529	1.030	13.311	0.275	0.378	0.501	1.149	21.237	0.272	0.371	0.500	1.179	21.616
Health	Uni-modal	12	1.595	0.808	1.113	2.599	252.012	1.051	0.756	0.975	4.069	371.454	1.900	1.008	1.278	6.208	1054.818
		24	1.778	0.835	1.170	2.742	312.129	1.493	0.933	1.176	4.818	434.785	1.946	0.973	1.287	4.194	322.873
		36	1.759	0.850	1.241	2.738	263.854	1.661	0.980	1.252	5.182	426.708	2.029	1.013	1.352	4.495	346.381
		48	1.818	0.899	1.299	2.964	278.936	1.737	0.969	1.285	4.775	392.270	2.054	1.026	1.379	4.356	305.131
		Avg	1.737	0.848	1.206	2.761	276.733	1.486	0.909	1.172	4.711	406.304	1.982	1.005	1.324	4.813	507.301
	MM-TSFLib	12	1.403	0.763	1.061	2.065	64.534	0.978	0.685	0.930	3.371	273.283	1.406	0.915	1.141	4.787	421.324
		24	1.544	0.782	1.114	2.167	68.258	1.272	0.804	1.073	3.538	212.521	1.730	0.975	1.257	4.258	251.992
		36	1.600	0.824	1.185	2.264	56.729	1.344	0.828	1.121	3.768	222.549	1.769	0.944	1.267	3.785	205.906
		48	1.617	0.830	1.222	2.368	87.198	1.416	0.852	1.163	3.913	243.392	1.793	0.960	1.286	3.626	178.720
		Avg	1.541	0.800	1.145	2.216	69.180	1.252	0.792	1.072	3.647	237.936	1.675	0.949	1.238	4.114	264.486
	TaTS (ours)	12	1.273	0.742	1.027	2.702	159.975	0.966	0.671	0.925	3.309	294.367	1.211	0.794	1.035	3.570	236.037
		24	1.421	0.788	1.090	3.221	254.155	1.264	0.823	1.080	4.068	289.731	1.414	0.827	1.107	3.160	130.456
		36	1.449	0.787	1.133	2.812	148.843	1.320	0.801	1.110	3.885	280.248	1.497	0.851	1.165	3.274	133.041
		48	1.505	0.832	1.183	2.990	186.495	1.426	0.868	1.164	4.140	264.871	1.562	0.878	1.209	3.225	121.440
		Avg	1.412	0.787	1.108	2.931	187.367	1.244	0.791	1.070	3.851	282.304	1.421	0.838	1.129	3.307	155.243

Table 24: Full forecasting results for the Security, Social Good, and Traffic datasets using DLinear, FEDformer, and FiLM as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Avg: the average results across all prediction lengths.

Models			DLinear (2023)					FEDformer (2022b)					FiLM (2022a)				
Method			MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Security	Uni-modal	6	107.046	4.531	10.346	3.489	324.650	112.106	4.830	10.588	4.456	571.690	115.130	5.587	10.730	5.029	637.394
		8	107.700	4.649	10.378	2.992	295.719	113.897	5.200	10.672	3.223	355.929	112.097	5.034	10.588	3.228	336.503
		10	109.360	4.759	10.458	2.449	216.866	117.484	5.467	10.839	2.563	216.459	112.267	4.901	10.596	2.310	188.201
		12	112.343	4.904	10.599	1.980	149.507	114.452	5.135	10.698	2.697	329.415	122.711	6.425	11.077	3.554	437.883
		Avg	109.112	4.711	10.445	2.728	246.685	114.485	5.158	10.699	3.235	368.373	115.551	5.487	10.748	3.530	399.995
	MM-TSFLib	6	106.121	4.545	10.301	3.788	386.715	109.854	4.690	10.481	4.252	541.638	105.809	4.755	10.286	4.286	525.309
		8	107.445	4.670	10.366	3.101	319.555	114.833	5.233	10.716	3.119	330.374	108.045	4.638	10.394	2.727	249.934
		10	108.713	4.758	10.427	2.613	251.113	115.261	5.294	10.736	2.563	233.233	111.391	4.843	10.554	1.953	137.888
		12	109.848	4.876	10.481	2.373	227.133	115.001	5.211	10.724	2.558	291.461	111.541	5.354	10.561	3.023	363.599
		Avg	108.032	4.712	10.394	2.969	296.129	113.737	5.107	10.664	3.123	349.177	109.197	4.897	10.449	2.997	319.183
	TaTS (ours)	6	106.015	4.516	10.296	3.850	404.799	106.015	4.532	10.296	4.542	597.429	105.482	4.511	10.270	4.024	451.366
		8	107.477	4.623	10.367	3.050	312.447	107.678	4.618	10.377	3.303	371.986	107.657	4.792	10.376	3.150	310.920
		10	108.505	4.728	10.417	2.632	260.096	107.301	4.885	10.359	3.138	375.009	109.886	4.771	10.483	2.338	193.865
		12	109.717	4.836	10.475	2.336	224.134	108.506	4.837	10.417	2.738	331.710	108.375	4.870	10.410	2.549	267.339
		Avg	107.928	4.676	10.389	2.967	300.369	107.375	4.718	10.362	3.430	419.034	107.850	4.736	10.385	3.015	305.873
Social Good	Uni-modal	6	1.018	0.627	0.859	1.503	19.120	0.821	0.386	0.649	1.086	28.066	1.123	0.604	0.878	2.432	149.647
		8	1.137	0.702	0.929	1.607	19.248	0.929	0.451	0.726	1.061	17.701	1.116	0.542	0.841	2.275	128.188
		10	1.210	0.755	0.972	1.732	21.287	1.059	0.478	0.784	1.469	52.985	1.154	0.601	0.882	1.823	42.492
		12	1.238	0.763	0.982	1.705	20.522	1.105	0.588	0.846	1.876	76.675	1.653	0.869	1.125	2.998	140.138
		Avg	1.151	0.712	0.935	1.637	20.044	0.979	0.476	0.751	1.373	43.857	1.261	0.654	0.931	2.382	115.116
	MM-TSFLib	6	0.946	0.583	0.810	1.481	21.957	0.816	0.395	0.667	1.182	33.446	1.070	0.529	0.824	2.269	159.103
		8	1.095	0.678	0.904	1.596	20.076	0.910	0.438	0.717	1.010	15.845	1.120	0.584	0.869	2.138	83.150
		10	1.128	0.709	0.924	1.713	22.953	1.032	0.456	0.757	1.395	53.857	1.128	0.539	0.839	2.235	120.886
		12	1.164	0.724	0.940	1.655	20.260	1.091	0.560	0.838	1.737	71.467	1.624	0.852	1.111	3.005	149.026
		Avg	1.083	0.673	0.894	1.611	21.312	0.962	0.462	0.745	1.331	43.654	1.236	0.626	0.911	2.412	128.041
	TaTS (ours)	6	0.859	0.516	0.740	1.453	29.534	0.746	0.365	0.620	0.983	23.097	0.992	0.588	0.834	1.623	30.115
		8	0.963	0.592	0.812	1.582	29.073	0.880	0.448	0.701	1.221	34.945	1.001	0.550	0.806	1.609	28.399
		10	1.118	0.703	0.917	1.711	23.312	0.944	0.453	0.720	1.138	28.381	1.065	0.583	0.837	1.447	17.661
		12	1.085	0.676	0.888	1.657	24.350	0.983	0.453	0.718	1.315	51.258	1.358	0.782	1.025	1.920	27.141
		Avg	1.006	0.622	0.839	1.601	26.567	0.888	0.430	0.690	1.164	34.420	1.104	0.626	0.876	1.650	25.829
Traffic	Uni-modal	6	0.221	0.358	0.461	0.357	0.549	0.202	0.294	0.416	0.285	0.377	0.202	0.302	0.426	0.346	0.682
		8	0.220	0.357	0.458	0.355	0.552	0.184	0.234	0.364	0.259	0.461	0.203	0.332	0.436	0.341	0.564
		10	0.217	0.347	0.451	0.358	0.601	0.198	0.251	0.386	0.271	0.474	0.203	0.340	0.438	0.323	0.447
		12	0.261	0.374	0.499	0.395	0.663	0.237	0.275	0.410	0.315	0.600	0.250	0.280	0.426	0.347	0.719
		Avg	0.230	0.359	0.467	0.366	0.591	0.205	0.264	0.394	0.283	0.478	0.215	0.314	0.431	0.339	0.603
	MM-TSFLib	6	0.204	0.332	0.439	0.321	0.465	0.180	0.245	0.372	0.258	0.408	0.197	0.294	0.419	0.339	0.664
		8	0.202	0.335	0.435	0.320	0.448	0.178	0.225	0.352	0.253	0.458	0.195	0.322	0.427	0.332	0.540
		10	0.205	0.325	0.435	0.320	0.478	0.184	0.234	0.364	0.258	0.446	0.195	0.328	0.428	0.312	0.424
		12	0.225	0.329	0.451	0.351	0.602	0.228	0.247	0.388	0.292	0.570	0.240	0.258	0.403	0.315	0.631
		Avg	0.209	0.330	0.440	0.328	0.498	0.193	0.238	0.369	0.265	0.471	0.207	0.300	0.419	0.325	0.565
	TaTS (ours)	6	0.184	0.312	0.412	0.301	0.435	0.159	0.208	0.329	0.228	0.355	0.157	0.228	0.351	0.254	0.426
		8	0.185	0.302	0.409	0.308	0.500	0.159	0.209	0.329	0.230	0.368	0.162	0.260	0.370	0.266	0.401
		10	0.184	0.297	0.403	0.309	0.524	0.160	0.206	0.323	0.229	0.370	0.169	0.269	0.380	0.262	0.358
		12	0.199	0.291	0.413	0.309	0.489	0.213	0.224	0.368	0.269	0.518	0.215	0.236	0.383	0.298	0.612
		Avg	0.188	0.300	0.409	0.307	0.487	0.173	0.212	0.337	0.239	0.403	0.176	0.248	0.371	0.270	0.449

Table 25: Full forecasting results for the Agriculture, Climate, and Economy datasets using Autoformer, Informer, and Transformer as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Avg: the average results across all prediction lengths.

Models			Autoformer (2021)					Informer (2021)					Transformer (2017)				
	Method		MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Agriculture	Uni-modal	6	0.109	0.255	0.329	0.116	0.022	0.451	0.557	0.626	0.240	0.071	0.229	0.326	0.420	0.133	0.032
		8	0.135	0.278	0.366	0.126	0.026	0.569	0.633	0.702	0.270	0.087	0.328	0.432	0.502	0.177	0.045
		10	0.173	0.311	0.413	0.138	0.031	0.618	0.633	0.724	0.263	0.088	0.358	0.422	0.510	0.166	0.045
		12	0.213	0.345	0.457	0.149	0.036	0.756	0.698	0.789	0.284	0.101	0.500	0.555	0.633	0.224	0.064
		Avg	0.158	0.297	0.391	0.132	0.029	0.599	0.630	0.710	0.264	0.087	0.354	0.434	0.516	0.175	0.046
	MM-TSFLib	6	0.095	0.221	0.306	0.100	0.018	0.218	0.352	0.422	0.148	0.032	0.197	0.319	0.392	0.133	0.029
		8	0.143	0.278	0.372	0.122	0.025	0.306	0.429	0.496	0.179	0.044	0.205	0.303	0.384	0.121	0.027
		10	0.176	0.311	0.416	0.137	0.031	0.301	0.398	0.480	0.160	0.040	0.215	0.332	0.411	0.135	0.030
		12	0.217	0.341	0.453	0.144	0.034	0.428	0.479	0.579	0.190	0.054	0.378	0.453	0.531	0.179	0.048
		Avg	0.158	0.288	0.387	0.126	0.027	0.313	0.414	0.494	0.169	0.042	0.249	0.352	0.429	0.142	0.034
	TaTS (ours)	6	0.076	0.205	0.269	0.092	0.014	0.162	0.265	0.342	0.107	0.022	0.150	0.348	0.387	0.166	0.034
		8	0.101	0.234	0.315	0.105	0.019	0.213	0.311	0.392	0.124	0.028	0.192	0.298	0.374	0.120	0.025
		10	0.138	0.299	0.371	0.134	0.026	0.296	0.388	0.465	0.154	0.038	0.209	0.296	0.384	0.114	0.026
		12	0.186	0.324	0.425	0.141	0.030	0.349	0.426	0.506	0.167	0.044	0.213	0.310	0.401	0.121	0.025
		Avg	0.125	0.266	0.345	0.118	0.022	0.255	0.348	0.426	0.138	0.033	0.191	0.313	0.387	0.130	0.028
Climate	Uni-modal	6	1.116	0.861	1.056	4.456	519.418	1.084	0.829	1.041	1.617	15.451	1.032	0.817	1.016	1.656	13.521
		8	1.117	0.856	1.057	3.329	177.957	1.087	0.829	1.043	2.464	66.852	1.135	0.856	1.065	1.868	22.687
		10	1.170	0.886	1.081	3.059	106.074	1.117	0.849	1.056	2.071	49.757	1.103	0.844	1.049	2.355	81.661
		12	1.123	0.855	1.059	3.364	125.779	1.150	0.859	1.071	2.557	94.732	1.100	0.841	1.048	1.663	24.078
		Avg	1.131	0.865	1.063	3.552	232.307	1.110	0.841	1.053	2.177	56.698	1.092	0.839	1.044	1.885	35.487
	MM-TSFLib	6	1.021	0.817	1.010	2.871	82.634	1.019	0.811	1.009	2.844	134.946	0.962	0.771	0.981	2.030	23.607
		8	1.039	0.819	1.018	3.018	99.283	0.970	0.772	0.985	2.210	43.152	0.991	0.783	0.995	1.976	22.312
		10	1.074	0.838	1.035	2.783	92.522	1.006	0.794	1.002	2.311	67.013	1.026	0.790	1.010	2.755	87.765
		12	1.078	0.836	1.038	2.731	78.154	1.009	0.791	0.999	2.499	86.993	1.011	0.789	1.000	1.895	27.637
		Avg	1.053	0.827	1.025	2.851	88.148	1.001	0.792	0.999	2.466	83.026	0.998	0.783	0.996	2.164	40.330
	TaTS (ours)	6	0.880	0.741	0.938	2.222	37.958	0.881	0.741	0.939	2.217	57.260	0.859	0.728	0.926	1.970	35.573
		8	0.937	0.768	0.968	2.136	36.109	0.909	0.749	0.953	1.981	29.665	0.913	0.761	0.955	2.524	73.564
		10	1.027	0.817	1.011	2.260	31.311	0.973	0.771	0.983	2.020	27.051	0.976	0.767	0.985	2.179	31.989
		12	1.075	0.831	1.033	2.317	35.133	0.958	0.764	0.974	1.727	15.480	0.930	0.757	0.960	1.871	23.016
		Avg	0.980	0.789	0.987	2.234	35.128	0.930	0.756	0.962	1.986	32.364	0.920	0.753	0.957	2.136	41.035
Economy	Uni-modal	6	0.083	0.222	0.288	0.077	0.010	0.877	0.896	0.930	0.308	0.102	0.276	0.444	0.517	0.150	0.031
		8	0.069	0.210	0.263	0.073	0.008	1.606	1.238	1.260	0.425	0.187	0.676	0.797	0.816	0.274	0.078
		10	0.070	0.209	0.261	0.072	0.008	1.409	1.153	1.179	0.395	0.162	0.601	0.750	0.768	0.257	0.069
		12	0.062	0.186	0.245	0.064	0.007	1.407	1.153	1.183	0.396	0.163	0.781	0.854	0.879	0.293	0.091
		Avg	0.071	0.207	0.264	0.071	0.008	1.325	1.110	1.138	0.381	0.153	0.584	0.711	0.745	0.243	0.067
	MM-TSFLib	6	0.049	0.173	0.221	0.060	0.006	0.293	0.490	0.531	0.167	0.033	0.110	0.285	0.322	0.096	0.012
		8	0.045	0.171	0.211	0.060	0.005	0.445	0.643	0.660	0.220	0.051	0.157	0.359	0.389	0.122	0.018
		10	0.071	0.214	0.267	0.075	0.009	0.471	0.664	0.680	0.227	0.054	0.240	0.450	0.483	0.154	0.028
		12	0.068	0.209	0.260	0.073	0.008	0.518	0.674	0.715	0.231	0.060	0.347	0.569	0.584	0.195	0.040
		Avg	0.058	0.192	0.240	0.067	0.007	0.432	0.618	0.646	0.211	0.049	0.213	0.416	0.445	0.142	0.025
	TaTS (ours)	6	0.021	0.115	0.144	0.040	0.002	0.247	0.472	0.488	0.161	0.028	0.029	0.137	0.169	0.047	0.003
		8	0.023	0.119	0.150	0.041	0.003	0.166	0.369	0.396	0.125	0.018	0.039	0.162	0.192	0.055	0.004
		10	0.024	0.122	0.153	0.042	0.003	0.400	0.610	0.626	0.209	0.046	0.092	0.266	0.299	0.091	0.010
		12	0.026	0.127	0.161	0.044	0.003	0.385	0.596	0.617	0.203	0.044	0.156	0.364	0.389	0.123	0.017
		Avg	0.024	0.121	0.152	0.042	0.003	0.299	0.512	0.532	0.174	0.034	0.079	0.232	0.262	0.079	0.009

Table 26: Full forecasting results for the Energy, Environment, and Health datasets using Autoformer, Informer, and Transformer as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Avg: the average results across all prediction lengths.

Models			Autoformer (2021)					Informer (2021)					Transformer (2017)				
Method			MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Energy	Uni-modal	12	0.161	0.282	0.362	1.403	24.893	0.165	0.289	0.373	1.491	35.971	0.124	0.247	0.320	1.021	8.908
		24	0.279	0.416	0.509	2.632	158.931	0.248	0.380	0.475	2.916	185.671	0.291	0.403	0.494	1.951	101.566
		36	0.364	0.464	0.564	2.384	93.988	0.368	0.492	0.585	4.022	356.146	0.329	0.435	0.542	3.964	428.707
		48	0.471	0.550	0.664	3.106	149.374	0.457	0.539	0.640	5.613	589.886	0.445	0.537	0.642	3.824	285.963
		Avg	0.319	0.428	0.525	2.381	106.797	0.309	0.425	0.518	3.511	291.918	0.297	0.405	0.500	2.690	206.286
	MM-TSFLib	12	0.164	0.297	0.369	1.720	78.617	0.166	0.291	0.372	1.667	36.449	0.127	0.270	0.334	1.278	11.692
		24	0.275	0.407	0.504	2.177	81.316	0.242	0.362	0.456	3.040	235.920	0.276	0.402	0.491	2.297	115.390
		36	0.362	0.464	0.561	2.176	88.219	0.342	0.467	0.566	3.221	271.106	0.316	0.439	0.530	3.504	272.971
		48	0.477	0.545	0.665	3.100	192.217	0.456	0.530	0.643	5.430	602.773	0.454	0.508	0.641	5.511	748.943
		Avg	0.320	0.428	0.525	2.293	110.092	0.301	0.413	0.509	3.340	286.562	0.293	0.405	0.499	3.147	287.249
	TaTS (ours)	12	0.153	0.291	0.365	1.490	33.553	0.145	0.271	0.347	1.118	11.872	0.126	0.252	0.324	1.036	12.192
		24	0.276	0.404	0.488	2.040	73.651	0.242	0.361	0.463	2.310	184.196	0.265	0.381	0.469	1.706	53.962
		36	0.360	0.467	0.555	2.167	80.434	0.301	0.415	0.514	3.658	379.160	0.301	0.419	0.515	2.804	209.452
		48	0.466	0.559	0.659	3.431	178.191	0.448	0.538	0.644	4.344	378.638	0.423	0.527	0.620	5.149	416.124
		Avg	0.314	0.430	0.517	2.282	91.457	0.284	0.396	0.492	2.857	238.466	0.279	0.395	0.482	2.674	172.933
Environment	Uni-modal	48	0.503	0.544	0.670	1.953	141.941	0.414	0.481	0.602	2.190	216.476	0.412	0.483	0.600	2.190	214.543
		96	0.594	0.605	0.743	2.015	135.052	0.467	0.520	0.644	2.454	290.858	0.458	0.511	0.639	2.608	340.210
		192	0.607	0.601	0.762	2.163	205.175	0.469	0.519	0.644	2.535	305.217	0.492	0.535	0.677	2.711	404.734
		336	0.690	0.643	0.823	2.624	307.413	0.487	0.529	0.693	2.726	355.026	0.479	0.517	0.688	2.824	389.196
		Avg	0.599	0.598	0.749	2.189	197.395	0.459	0.512	0.646	2.476	291.894	0.460	0.511	0.651	2.583	337.171
	MM-TSFLib	48	0.442	0.492	0.626	2.008	164.960	0.419	0.473	0.604	1.997	163.772	0.420	0.471	0.606	2.027	163.407
		96	0.456	0.505	0.645	1.930	154.161	0.426	0.477	0.616	2.074	173.217	0.426	0.485	0.615	2.380	252.997
		192	0.461	0.505	0.663	1.995	181.553	0.425	0.481	0.634	2.410	256.710	0.418	0.479	0.630	2.356	252.249
		336	0.447	0.506	0.666	1.994	172.427	0.427	0.489	0.651	2.283	225.380	0.435	0.487	0.657	2.551	282.514
		Avg	0.452	0.502	0.650	1.982	168.275	0.424	0.480	0.626	2.191	204.770	0.425	0.481	0.627	2.329	237.792
	TaTS (ours)	48	0.274	0.374	0.486	1.159	21.042	0.272	0.377	0.483	1.103	18.922	0.268	0.378	0.481	1.074	17.152
		96	0.286	0.387	0.509	1.183	21.118	0.287	0.401	0.507	1.040	15.636	0.272	0.391	0.496	1.028	15.508
		192	0.291	0.382	0.528	1.272	24.699	0.297	0.426	0.531	1.003	13.899	0.277	0.398	0.512	1.030	16.253
		336	0.288	0.403	0.534	1.122	20.057	0.286	0.419	0.533	0.989	13.846	0.287	0.420	0.534	1.006	15.226
		Avg	0.285	0.387	0.514	1.184	21.729	0.285	0.406	0.513	1.034	15.576	0.276	0.397	0.506	1.035	16.035
Health	Uni-modal	12	1.389	0.895	1.121	4.898	593.771	1.173	0.743	0.990	4.065	593.314	1.143	0.741	0.998	3.233	133.066
		24	2.328	1.191	1.476	6.117	859.160	1.215	0.766	1.042	3.728	389.282	1.480	0.786	1.096	2.435	59.228
		36	1.953	1.005	1.348	4.614	392.542	1.315	0.773	1.101	3.541	390.034	1.450	0.772	1.132	2.766	136.630
		48	2.179	1.064	1.410	4.865	379.673	1.408	0.809	1.137	3.445	337.635	1.439	0.806	1.137	2.834	125.016
		Avg	1.962	1.039	1.339	5.123	556.286	1.278	0.773	1.067	3.695	427.566	1.378	0.776	1.091	2.817	113.485
	MM-TSFLib	12	1.331	0.864	1.112	4.427	504.600	0.997	0.673	0.928	3.024	221.350	0.953	0.686	0.920	3.309	198.713
		24	1.454	0.868	1.138	3.681	181.137	1.209	0.740	1.046	3.372	257.237	1.315	0.762	1.071	2.833	137.728
		36	1.574	0.906	1.216	4.051	234.643	1.282	0.760	1.092	3.111	213.531	1.276	0.763	1.070	2.906	137.944
		48	1.616	0.911	1.235	3.884	201.678	1.371	0.785	1.137	3.146	234.342	1.330	0.780	1.109	2.769	125.761
		Avg	1.494	0.887	1.175	4.011	280.514	1.215	0.740	1.051	3.163	231.615	1.218	0.748	1.042	2.954	150.036
	TaTS (ours)	12	1.320	0.863	1.105	3.769	309.199	0.949	0.658	0.910	3.707	391.895	0.909	0.655	0.862	3.251	292.588
		24	1.467	0.885	1.159	3.485	152.650	1.130	0.736	1.020	3.897	352.680	1.187	0.728	1.030	3.143	192.685
		36	1.368	0.825	1.120	3.962	230.059	1.301	0.779	1.110	3.540	270.359	1.175	0.728	1.048	3.096	193.526
		48	1.483	0.871	1.180	4.108	279.227	1.354	0.833	1.143	3.962	372.090	1.297	0.762	1.113	3.074	185.199
		Avg	1.409	0.861	1.141	3.831	242.784	1.183	0.752	1.046	3.776	346.756	1.142	0.718	1.013	3.141	216.000

Table 27: Full forecasting results for the Security, Social Good, and Traffic datasets using Autoformer, Informer, and Transformer as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Avg: the average results across all prediction lengths.

Models			Autoformer (2021)					Informer (2021)					Transformer (2017)				
Method			MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Security	Uni-modal	6	115.544	5.268	10.749	2.437	185.108	133.168	6.626	11.540	1.591	19.155	126.925	6.203	11.266	2.547	120.160
		8	113.355	4.967	10.647	2.888	298.107	134.383	6.804	11.592	1.236	6.780	132.905	6.641	11.528	1.209	14.174
		10	114.407	4.984	10.696	2.164	153.069	131.382	6.631	11.462	1.483	26.411	128.820	6.443	11.350	1.539	32.792
		12	117.801	5.253	10.854	2.692	326.651	128.201	6.430	11.323	1.408	26.498	136.753	7.039	11.694	1.168	4.854
		Avg	115.277	5.118	10.736	2.545	240.734	131.784	6.623	11.479	1.429	19.711	131.351	6.582	11.460	1.616	42.995
	MM-TSFLib	6	108.841	4.861	10.433	3.004	246.068	127.216	6.197	11.279	2.326	99.099	127.277	6.233	11.282	2.592	135.752
		8	113.693	5.031	10.663	2.799	265.988	128.914	6.402	11.354	1.660	40.618	126.589	6.227	11.251	2.010	84.511
		10	112.545	5.098	10.609	1.885	120.031	128.775	6.434	11.348	1.532	38.764	127.986	6.368	11.313	1.520	32.213
		12	110.699	4.902	10.521	2.177	199.450	130.907	6.626	11.441	1.443	33.523	132.033	6.685	11.491	1.217	11.881
		Avg	111.445	4.973	10.556	2.466	207.884	128.953	6.415	11.356	1.740	53.001	128.471	6.378	11.334	1.835	66.089
	TaTS (ours)	6	107.430	4.658	10.365	4.255	528.013	127.814	6.269	11.306	2.263	110.185	122.803	5.927	11.082	2.966	185.980
		8	107.108	4.750	10.349	3.531	455.878	125.990	6.217	11.225	2.390	135.504	123.882	6.057	11.130	2.505	151.979
		10	110.061	4.891	10.491	3.615	562.774	125.737	6.248	11.213	2.231	134.082	125.666	6.262	11.210	2.232	128.702
		12	109.361	4.847	10.458	3.060	457.480	127.103	6.369	11.274	1.885	86.102	125.971	6.290	11.224	1.899	90.926
		Avg	108.490	4.787	10.416	3.615	501.036	126.661	6.276	11.255	2.192	116.468	124.581	6.134	11.162	2.401	139.397
Social Good	Uni-modal	6	1.234	0.684	0.973	1.910	69.347	0.773	0.425	0.668	0.872	13.761	0.848	0.427	0.684	1.208	27.858
		8	1.236	0.664	0.956	1.998	80.017	0.871	0.449	0.708	0.933	11.089	0.877	0.460	0.719	1.520	56.020
		10	1.332	0.708	1.026	2.116	93.499	0.910	0.498	0.755	0.905	6.360	0.976	0.541	0.783	1.725	63.227
		12	1.312	0.749	1.046	2.231	75.925	0.926	0.644	0.818	1.028	7.619	0.938	0.508	0.750	1.389	28.551
		Avg	1.278	0.701	1.000	2.064	79.697	0.870	0.504	0.737	0.934	9.707	0.910	0.484	0.734	1.460	43.914
	MM-TSFLib	6	1.200	0.664	0.954	1.890	66.499	0.772	0.414	0.666	0.726	8.039	0.784	0.422	0.673	0.938	18.507
		8	1.175	0.589	0.891	1.935	84.135	0.829	0.405	0.673	0.746	6.869	0.845	0.426	0.669	1.056	19.505
		10	1.268	0.689	1.002	1.756	44.172	0.876	0.466	0.724	0.855	6.248	0.913	0.486	0.731	1.252	25.176
		12	1.272	0.739	1.032	2.048	56.789	0.879	0.541	0.765	0.888	7.772	0.882	0.510	0.744	1.021	13.844
		Avg	1.229	0.670	0.970	1.907	62.899	0.839	0.457	0.707	0.804	7.232	0.856	0.461	0.704	1.067	19.258
	TaTS (ours)	6	1.057	0.564	0.877	1.451	33.099	0.724	0.448	0.660	0.765	7.156	0.740	0.375	0.616	0.700	3.824
		8	1.184	0.686	0.954	1.476	20.587	0.788	0.463	0.696	0.890	8.039	0.805	0.393	0.632	0.828	11.467
		10	1.278	0.714	0.986	1.578	21.226	0.828	0.468	0.691	0.880	8.487	0.842	0.485	0.700	1.062	11.719
		12	1.261	0.699	0.979	1.544	21.227	0.899	0.455	0.698	0.785	4.917	0.842	0.424	0.650	0.777	5.973
		Avg	1.195	0.666	0.949	1.512	24.035	0.810	0.459	0.686	0.830	7.150	0.807	0.419	0.649	0.842	8.246
Traffic	Uni-modal	6	0.201	0.295	0.416	0.316	0.542	0.197	0.352	0.434	0.303	0.328	0.203	0.344	0.438	0.299	0.307
		8	0.205	0.296	0.419	0.299	0.440	0.202	0.358	0.440	0.320	0.369	0.224	0.364	0.460	0.302	0.285
		10	0.200	0.297	0.413	0.310	0.479	0.196	0.351	0.430	0.296	0.314	0.209	0.353	0.445	0.298	0.295
		12	0.241	0.303	0.448	0.350	0.653	0.213	0.358	0.448	0.326	0.397	0.200	0.323	0.426	0.316	0.416
		Avg	0.212	0.298	0.424	0.319	0.528	0.202	0.355	0.438	0.311	0.352	0.209	0.346	0.442	0.304	0.326
	MM-TSFLib	6	0.195	0.248	0.390	0.247	0.360	0.166	0.297	0.387	0.285	0.391	0.164	0.291	0.384	0.271	0.340
		8	0.204	0.274	0.401	0.277	0.404	0.169	0.306	0.393	0.285	0.372	0.172	0.305	0.395	0.274	0.318
		10	0.207	0.274	0.409	0.268	0.407	0.169	0.305	0.391	0.282	0.358	0.169	0.297	0.391	0.283	0.393
		12	0.241	0.292	0.420	0.343	0.795	0.183	0.290	0.392	0.292	0.414	0.181	0.288	0.392	0.287	0.389
		Avg	0.212	0.272	0.405	0.284	0.492	0.172	0.299	0.391	0.286	0.384	0.171	0.295	0.390	0.279	0.360
	TaTS (ours)	6	0.161	0.225	0.356	0.253	0.440	0.159	0.282	0.375	0.266	0.337	0.159	0.274	0.373	0.269	0.384
		8	0.167	0.237	0.353	0.258	0.416	0.161	0.289	0.378	0.270	0.340	0.156	0.268	0.367	0.266	0.386
		10	0.163	0.214	0.339	0.250	0.477	0.157	0.276	0.368	0.274	0.399	0.157	0.270	0.367	0.267	0.383
		12	0.217	0.242	0.379	0.293	0.575	0.181	0.279	0.387	0.289	0.429	0.183	0.285	0.391	0.292	0.423
		Avg	0.177	0.229	0.357	0.264	0.477	0.164	0.281	0.377	0.275	0.376	0.164	0.274	0.374	0.274	0.394

Table 28: Full forecasting results for various datasets using different time series modeling methods. Our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Avg: the average results across all prediction lengths.

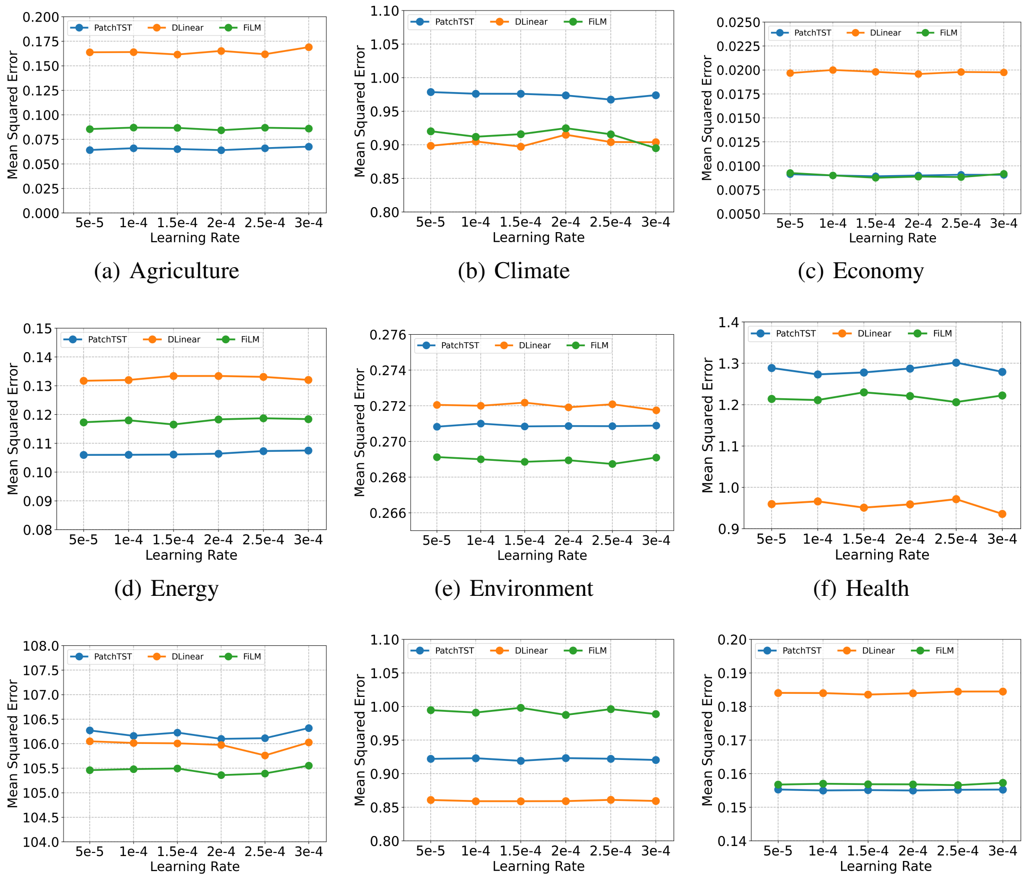
Methods			TaTS (ours) + iTransformer		TaTS (ours) + PatchTST		TaTS (ours) + FiLM		N-BEATS (2020)		N-HiTS (2022)		TCN (2018)		ChatTime (2025)		GPT4MTS (2024)	
Datasets			MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE	MSE	MAE
Time-MMD (2024a)	Agriculture	6	0.067	0.184	0.066	0.171	0.087	0.205	2.436	1.210	2.274	1.134	3.957	1.770	0.502	0.441	0.197	0.292
		8	0.094	0.210	0.096	0.217	0.110	0.223	3.671	1.446	1.575	0.866	5.078	1.919	0.510	0.449	0.352	0.426
		10	0.122	0.251	0.126	0.260	0.146	0.249	3.078	1.416	1.441	0.910	4.464	1.866	0.505	0.445	0.358	0.413
		12	0.153	0.271	0.166	0.292	0.196	0.328	3.883	1.759	2.119	1.217	3.173	1.633	0.517	0.452	0.404	0.444
		Avg	0.109	0.229	0.114	0.235	0.135	0.251	3.267	1.458	1.852	1.032	4.168	1.797	0.508	0.447	0.327	0.393
	Climate	6	1.020	0.797	0.976	0.782	0.912	0.758	1.123	0.894	1.114	0.881	1.137	0.875	1.507	1.007	1.062	0.844
		8	1.025	0.797	0.995	0.803	0.917	0.751	1.070	0.844	0.981	0.791	1.046	0.804	1.524	1.012	1.177	0.893
		10	1.033	0.808	1.022	0.796	0.947	0.759	1.093	0.850	1.152	0.877	1.043	0.857	1.578	1.027	1.100	0.863
		12	1.033	0.812	1.022	0.810	1.005	0.821	1.085	0.856	1.166	0.884	1.167	0.926	1.664	1.031	1.169	0.893
		Avg	1.028	0.804	1.004	0.798	0.945	0.772	1.093	0.861	1.103	0.858	1.098	0.866	1.568	1.019	1.127	0.873
	Economy	6	0.008	0.077	0.009	0.080	0.009	0.080	0.727	0.782	0.224	0.432	5.390	2.315	0.042	0.156	0.013	0.091
		8	0.008	0.077	0.008	0.078	0.009	0.079	0.874	0.882	0.675	0.793	5.811	2.406	0.045	0.157	0.014	0.096
		10	0.009	0.079	0.009	0.079	0.009	0.079	0.999	0.849	0.486	0.647	5.426	2.324	0.052	0.165	0.015	0.098
		12	0.008	0.076	0.009	0.080	0.009	0.081	1.438	1.166	0.389	0.465	5.556	2.352	0.059	0.188	0.016	0.101
		Avg	0.008	0.077	0.009	0.079	0.009	0.080	1.010	0.920	0.444	0.584	5.546	2.349	0.049	0.166	0.014	0.096
	Energy	12	0.106	0.234	0.106	0.234	0.118	0.245	0.146	0.271	0.195	0.336	0.165	0.318	0.128	0.253	0.117	0.244
		24	0.226	0.355	0.206	0.336	0.222	0.347	0.280	0.413	0.612	0.582	0.407	0.507	0.258	0.363	0.212	0.347
		36	0.306	0.411	0.305	0.412	0.311	0.414	0.431	0.482	0.380	0.474	0.512	0.569	0.361	0.465	0.328	0.424
		48	0.421	0.502	0.416	0.501	0.434	0.510	0.460	0.532	0.301	0.460	0.634	0.654	0.473	0.588	0.421	0.497
		Avg	0.265	0.376	0.258	0.371	0.271	0.379	0.329	0.424	0.372	0.463	0.430	0.512	0.305	0.417	0.269	0.378
	Environment	48	0.268	0.370	0.271	0.377	0.269	0.373	0.448	0.504	0.440	0.523	0.805	0.693	0.583	0.594	0.312	0.390
		96	0.267	0.370	0.279	0.376	0.279	0.377	0.540	0.582	0.421	0.522	0.738	0.686	0.575	0.591	0.345	0.408
		192	0.272	0.366	0.272	0.366	0.271	0.367	0.522	0.592	0.635	0.660	1.466	0.982	0.577	0.594	0.358	0.440
		336	0.261	0.369	0.269	0.366	0.267	0.366	0.563	0.614	0.593	0.628	0.407	0.490	0.585	0.599	0.377	0.453
		Avg	0.267	0.369	0.273	0.371	0.272	0.371	0.518	0.573	0.522	0.583	0.854	0.713	0.580	0.594	0.348	0.422
	Health	12	0.939	0.649	0.990	0.659	1.211	0.794	1.572	0.838	1.723	0.866	2.484	1.027	1.482	0.802	1.157	0.704
		24	1.251	0.712	1.288	0.764	1.414	0.827	1.680	0.981	1.621	0.905	2.072	1.070	1.645	0.956	1.743	0.904
		36	1.489	0.781	1.397	0.780	1.497	0.851	1.834	0.980	1.687	0.908	1.557	0.859	1.732	0.937	1.950	0.938
		48	1.581	0.834	1.456	0.808	1.562	0.878	1.556	0.952	1.635	0.911	1.639	0.922	1.813	0.942	2.217	0.957
		Avg	1.315	0.744	1.283	0.753	1.421	0.838	1.660	0.938	1.666	0.898	1.938	0.970	1.668	0.909	1.766	0.875
	Security	6	107.113	4.856	106.160	4.696	105.482	4.511	131.917	6.866	135.416	6.896	129.616	6.801	130.751	6.854	118.425	5.102
		8	112.560	5.204	108.803	5.052	107.657	4.792	113.095	6.287	144.874	7.780	128.578	6.936	134.526	6.875	118.952	5.106
		10	113.789	5.227	111.110	5.090	109.886	4.771	163.555	7.344	156.898	6.797	160.129	7.077	131.632	6.895	119.521	5.253
		12	114.754	5.318	112.699	5.237	108.375	4.870	111.694	5.974	115.307	6.437	128.062	6.676	135.513	6.923	120.732	5.331
		Avg	112.054	5.151	109.693	5.019	107.850	4.736	130.065	6.618	138.124	6.978	136.596	6.873	133.106	6.887	119.407	5.198
	Social Good	6	0.942	0.398	0.923	0.436	0.992	0.588	1.752	0.654	1.446	0.626	1.535	0.917	1.213	0.608	1.214	0.485
		8	0.967	0.433	0.900	0.461	1.001	0.550	0.952	0.551	1.033	0.531	1.129	0.935	1.252	0.621	1.422	0.560
		10	0.994	0.463	0.996	0.461	1.065	0.583	1.116	0.627	1.112	0.594	1.208	0.996	1.278	0.667	1.264	0.572
		12	1.045	0.514	1.069	0.501	1.358	0.782	1.445	0.827	1.498	0.846	1.385	0.996	1.313	0.712	1.757	0.622
		Avg	0.987	0.452	0.972	0.465	1.104	0.626	1.316	0.665	1.272	0.649	1.314	0.961	1.264	0.652	1.414	0.559
	Traffic	6	0.174	0.218	0.155	0.204	0.157	0.228	0.352	0.409	0.295	0.372	0.779	0.775	0.369	0.435	0.185	0.227
		8	0.177	0.213	0.162	0.210	0.162	0.260	0.329	0.467	0.279	0.385	0.674	0.704	0.361	0.432	0.190	0.240
		10	0.186	0.225	0.167	0.214	0.169	0.269	0.342	0.474	0.281	0.404	0.702	0.758	0.363	0.427	0.189	0.246
		12	0.213	0.212	0.361	0.241	0.215	0.236	0.364	0.505	0.217	0.368	0.675	0.739	0.359	0.422	0.219	0.272
		Avg	0.187	0.217	0.172	0.209	0.176	0.248	0.347	0.464	0.268	0.382	0.708	0.744	0.363	0.429	0.195	0.246
FNSPID (2024)	Delta Airlines (DAL)	6	0.064	0.161	0.059	0.160	0.065	0.167	0.253	0.417	0.191	0.342	0.247	0.422	0.068	0.169	0.069	0.179
		12	0.110	0.233	0.116	0.224	0.126	0.235	0.320	0.470	0.260	0.416	0.341	0.509	0.128	0.235	0.118	0.223
		Avg	0.087	0.197	0.086	0.192	0.095	0.201	0.286	0.444	0.226	0.379	0.294	0.466	0.098	0.202	0.093	0.201
	IBM (IBM)	6	0.324	0.401	0.341	0.401	0.642	0.534	0.820	0.667	0.913	0.675	2.001	1.150	0.396	0.453	0.392	0.424
		12	0.804	0.602	0.758	0.580	1.140	0.856	1.390	0.887	1.517	0.937	1.870	1.096	0.807	0.619	0.886	0.627
		Avg	0.564	0.501	0.550	0.490	0.891	0.695	1.105	0.777	1.215	0.806	1.936	1.123	0.602	0.536	0.639	0.525
	JPMorgan Chase (JPM)	6	1.173	0.817	1.275	0.819	1.606	0.912	1.788	1.063	2.217	1.082	3.971	1.785	1.332	0.843	1.644	0.922
		12	2.214	1.124	2.470	1.161	3.421	1.281	3.050	1.287	4.635	1.383	3.557	1.637	2.742	1.244	2.622	1.323
		Avg	1.693	0.970	1.872	0.990	2.513	1.096	2.419	1.175	3.426	1.232	3.764	1.711	2.037	1.043	2.133	1.122
	NVIDIA (NVDA)	6	0.032	0.123	0.041	0.151	0.037	0.172	0.257	0.424	0.093	0.224	0.431	0.560	0.038	0.139	0.043	0.149
		12	0.054	0.159	0.055	0.162	0.063	0.177	0.288	0.445	0.151	0.301	0.483	0.587	0.067	0.183	0.066	0.170
		Avg	0.043	0.141	0.048	0.156	0.050	0.174	0.272	0.434	0.122	0.262	0.457	0.574	0.053	0.161	0.054	0.159
	Pfizer (PFE)	6	0.240	0.355	0.255	0.363	0.329	0.419	0.767	0.623	0.662	0.608	0.601	0.557	0.354	0.451	0.283	0.389
		12	0.412	0.476	0.439	0.482	0.567	0.535	0.586	0.520	0.987	0.718	0.654	0.561	0.462	0.503	0.456	0.490
		Avg	0.326	0.416	0.347	0.422	0.448	0.477	0.676	0.572	0.824	0.663	0.628	0.559	0.408	0.477	0.369	0.439
	Tesla (TSLA)	6	0.101	0.241	0.071	0.204	0.098	0.235	0.166	0.306	0.262	0.452	3.784	1.929	0.123	0.256	0.166	0.315
		12	0.183	0.321	0.245	0.390	0.122	0.253	0.210	0.358	0.247	0.381	3.168	1.773	0.192	0.343	0.196	0.292
		Avg	0.142	0.281	0.158	0.297	0.110	0.244	0.188	0.332	0.254	0.416	3.476	1.851	0.158	0.300	0.181	0.303
FNF (2024b)	Bitcoin Price	6	1.760	0.916	1.552	0.858	1.751	0.899	123.135	9.413	105.978	9.806	43.935	5.848	2.525	1.085	1.808	0.894
		8	2.147	1.006	1.998	0.964	2.458	1.080	126.985	9.703	163.110	10.690	53.318	6.412	3.352	1.163	2.521	1.050
		10	3.007	1.212	2.621	1.128	3.399	1.287	157.388	11.113	179.247	10.759	65.162	7.253	3.853	1.486	3.014	1.208
		12	3.521	1.313	3.185	1.229	3.491	1.304	159.445	11.192	187.741	10.884	68.887	7.464	4.631	1.641	3.542	1.456
		Avg	2.609	1.112	2.339	1.045	2.775	1.142	141.738	10.355	159.019	10.535	57.826	6.744	3.590	1.344	2.721	1.152
	Web Traffic	6	15.106	2.504	17.348	2.755	17.378	2.755	21.596	3.003	21.993	2.912	16.625	2.157	19.265	2.869	18.106	2.832
		8	18.474	2.740	17.715	2.625	16.11	2.600	19.330	2.754	21.001	2.828	20.144	2.826	21.724	2.924	18.421	2.745
		10	18.313	2.783	18.008	2.643	16.23	2.516	20.866	2.901	24.046	2.930	21.976	2.947	20.164	2.875	19.902	2.792
		12	19.084	2.823	18.783	2.590	22.721	3.217	27.141	3.409	26.011	3.374	27.759	3.439	21.841	2.969	20.611	2.942
		Avg	17.744	2.712	17.964	2.653	18.110	2.772	22.233	3.017	23.263	3.011	21.626	2.842	20.748	2.909	19.260	2.827
	Electricity Demand	6	0.262	0.379	0.257	0.374	0.260	0.375	0.385	0.470	0.338	0.443	0.436	0.506	0.510	0.544	0.271	0.388
		8	0.274	0.391	0.257	0.370	0.244	0.360	0.419	0.497	0.426	0.504	0.501	0.565	0.524	0.562	0.284	0.369
		10	0.288	0.405	0.173	0.266	0.252	0.366	0.407	0.494	0.335	0.454	0.558	0.582	0.536	0.571	0.292	0.398
		12	0.295	0.408	0.327	0.424	0.310	0.408	0.451	0.522	0.355	0.471	0.567	0.601	0.558	0.588	0.337	0.428
		Avg	0.280	0.396	0.254	0.358	0.266	0.377	0.416	0.496	0.364	0.468	0.516	0.564	0.532	0.566	0.296	0.395

E.4 Full Imputation Results

Table 29: Full imputation results for the Climate, Economy, and Traffic datasets using PatchTST, DLinear and FiLM as time series models. Compared to numerical-only unimodal modeling and MM-TSFLib, our TaTS framework seamlessly enhances existing time series models to effectively handle time series with concurrent texts. Promotion: the improvement of the best baseline.

Models		PatchTST (2023)					DLinear (2023)					FiLM (2022a)				
Metric		MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE	MSE	MAE	RMSE	MAPE	MSPE
Climate	Uni-modal	1.111	0.846	1.052	3.898	442.010	0.969	0.801	0.983	1.881	59.681	1.123	0.829	1.059	2.647	128.421
	MM-TSFLib	1.010	0.821	1.002	2.156	81.983	0.963	0.802	0.980	1.394	18.580	1.130	0.833	1.061	1.949	51.811
	TaTS (ours)	0.878	0.720	0.937	1.573	35.877	0.912	0.757	0.951	1.701	25.242	0.820	0.718	0.902	1.478	30.622
	Promotion	13.1%	12.3%	6.5%	27.0%	56.2%	5.3%	5.5%	3.0%	-22.0%	-35.9%	27.0%	13.4%	14.8%	24.2%	40.9%
Economy	Uni-modal	0.029	0.138	0.170	0.051	0.004	0.057	0.190	0.239	0.068	0.007	0.077	0.209	0.277	0.076	0.010
	MM-TSFLib	0.026	0.137	0.161	0.049	0.003	0.061	0.196	0.247	0.069	0.007	0.075	0.203	0.271	0.072	0.009
	TaTS (ours)	0.017	0.107	0.128	0.038	0.002	0.045	0.171	0.210	0.061	0.006	0.054	0.168	0.232	0.061	0.007
	Promotion	34.6%	21.9%	20.5%	22.4%	33.3%	21.1%	10.0%	12.1%	10.3%	14.3%	28.0%	17.2%	14.4%	15.3%	22.2%
Traffic	Uni-modal	0.210	0.339	0.444	0.358	0.600	0.245	0.417	0.489	0.430	0.720	0.175	0.311	0.409	0.343	0.508
	MM-TSFLib	0.189	0.341	0.428	0.391	0.690	0.179	0.335	0.419	0.362	0.630	0.169	0.288	0.396	0.316	0.545
	TaTS (ours)	0.131	0.248	0.331	0.312	0.647	0.134	0.297	0.352	0.266	0.270	0.137	0.242	0.354	0.281	0.388
	Promotion	30.7%	26.8%	22.7%	12.8%	-7.8%	25.1%	11.3%	16.0%	26.5%	57.1%	18.9%	16.0%	10.6%	11.1%	23.6%

E.5 Full Hyperparameter Study Results of Learning Rate



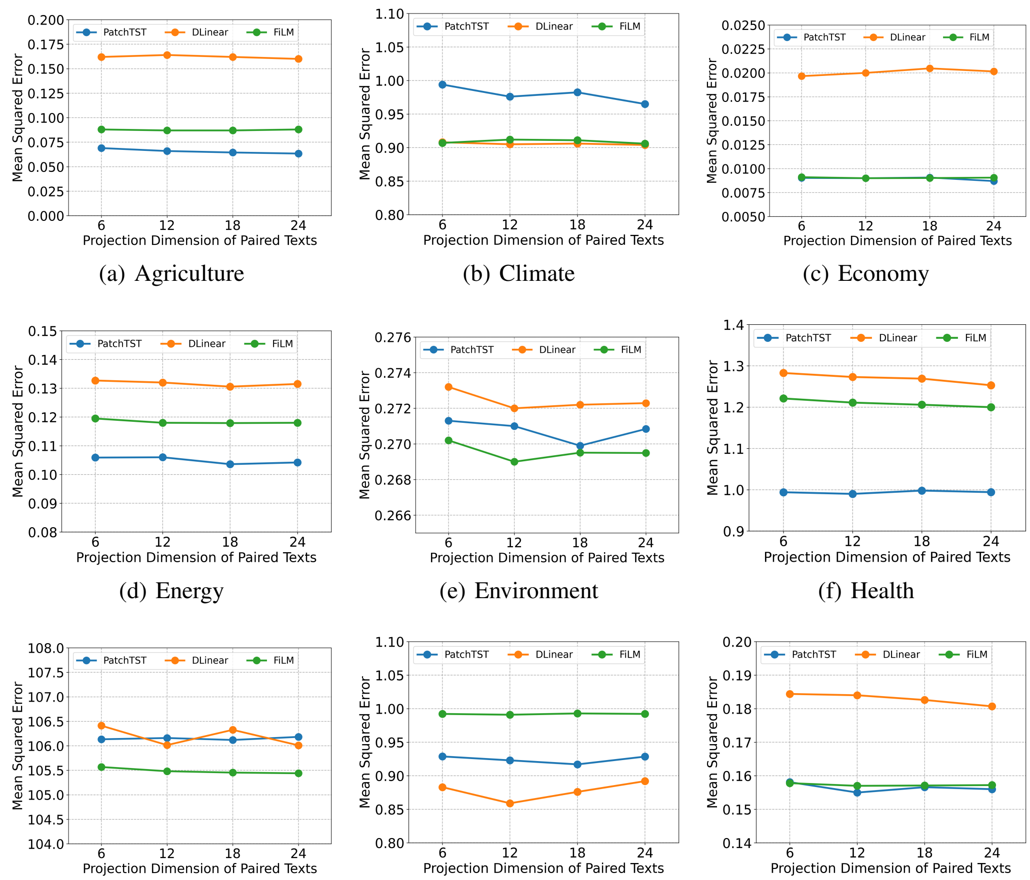
(a) Agriculture (b) Climate (c) Economy

(d) Energy (e) Environment (f) Health

(g) Security (h) Social Good (i) Traffic

Figure 11: Parameter study on the learning rate. We evaluate the impact of varying the learning rate in $\{0.00005, 0.0001, 0.00015, 0.0002, 0.00025, 0.0003\}$ by reporting the mean squared error (MSE) of our TaTS framework across datasets. The results demonstrate that TaTS maintains stable performance across different learning rate choices.

E.6 Full Hyperparameter Study Results of Text Embedding Dimension



(a) Agriculture (b) Climate (c) Economy

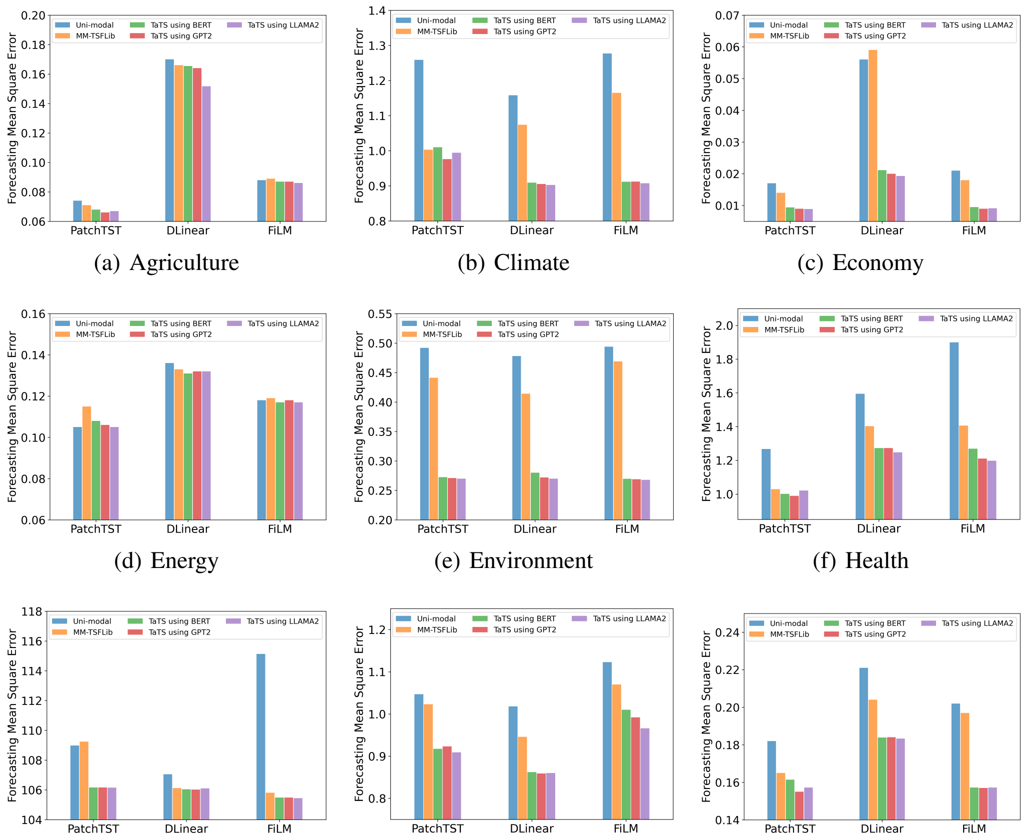
(d) Energy (e) Environment (f) Health

(g) Security (h) Social Good (i) Traffic

Figure 12: Parameter study on the projection dimension of paired texts. We vary the text projection dimension in $\{6, 12, 18, 24\}$ and report the mean squared error (MSE) of our TaTS framework across datasets. The results indicate that TaTS maintains robust performance across different choices of text projection dimensions.

E.7 Full Ablation Study Results Using Different Text Encoders

We conduct experiments to evaluate the performance of our TaTS with multiple language encoders. Specifically, we evaluation TaTS with BERT-110M[2], GPT2-1.5B[3] and LLaMA2-7B[4] as the language encoders. The results, presented in Figure 13, demonstrate that TaTS remains robust across different text encoders and consistently outperforms the baselines.



(a) Agriculture (b) Climate (c) Economy

(d) Energy (e) Environment (f) Health

(g) Security (h) Social Good (i) Traffic

Figure 13: Performance comparison of different text encoders within the TaTS framework. Specifically, we evaluate BERT-110M, GPT2-1.5B, and LLaMA2-7B across multiple datasets using PatchTST (transformer-based model), DLinear (linear-based model), and FiLM (frequency-based model). TaTS maintains relatively stable performance across various models and datasets.

In the main experiments, the text embeddings are obtained by a mean pooling over token embeddings. There are more advanced embedding techniques. To this end, we conducted an additional experiment using LLaMA-3.2-1B to generate sentence-level embeddings, while keeping all other settings the same. The results are shown below in Table 30.

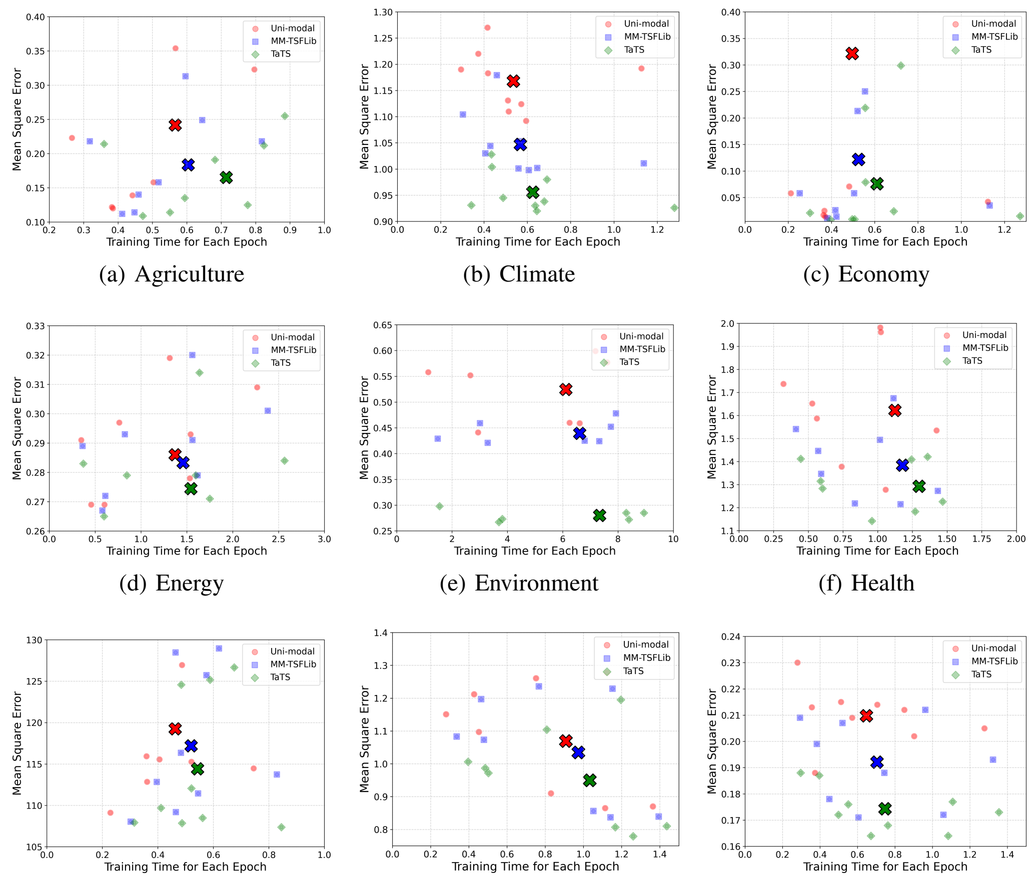
Table 30: Mean Square Error of TaTS forecasting with different text embedding methods.

Text Embedding Method	Agriculture	Climate	Economy	Security	Social Good	Traffic
GPT-2 average pooling (prediction length 6)	0.067	1.020	0.008	107.113	0.942	0.174
LLaMA-3.2-1B sentence embeddings (prediction length 6)	0.067	1.015	0.008	106.625	0.935	0.179
GPT-2 average pooling (prediction length 12)	0.153	1.033	0.008	114.754	1.045	0.213
LLaMA-3.2-1B sentence embeddings (prediction length 12)	0.152	1.021	0.008	114.219	1.025	0.209

[2] https://huggingface.co/google-bert/bert-base-uncased
[3] https://huggingface.co/openai-community/gpt2
[4] https://huggingface.co/meta-llama/Llama-2-7b

E.8 Full Efficiency Results: Computational Overhead vs. Performance Gain Trade-offs

We conduct experiments to analyze the efficiency of TaTS, with results presented in Figure 14. Each subfigure visualizes the training time per epoch and the forecasting mean squared error (MSE) for different time series models, represented as transparent colored scatter points. The average performance is computed and marked with cross markers: the green cross represents the average performance of TaTS, while the red and blue crosses indicate the average performance of the baseline models. As TaTS introduces a lightweight MLP and augments the original time series with auxiliary variables projected from paired texts, it incurs a slight computational overhead, with an average increase of $\sim 8\%$. Yet this trade-off results in a $\sim 14\%$ average improvement of forecasting MSE.



(a) Agriculture (b) Climate (c) Economy

(d) Energy (e) Environment (f) Health

(g) Security (h) Social Good (i) Traffic

Figure 14: Efficiency and forecasting performance comparison of uni-modal time-series modeling, MM-TSFLib, and our TaTS framework. While TaTS incurs a slight increase in training time due to the augmentation of auxiliary variables projected from paired texts, it significantly enhances forecasting accuracy, achieving a lower MSE.