RETHINKING MULTIMODAL TIME SERIES FORECASTING: TEXT MODALITIES NEED CONSTRAINED FUSION

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ABSTRACT

Recent advances in multimodal learning have motivated the integration of textual information into time series (TS) forecasting. However, most existing methods provide limited gains, often improving performance only in specific datasets or relying on architecture-specific designs that limit generalization. In this paper, we show that multimodal models with naive fusion strategies (e.g., simple addition or concatenation) often underperform unimodal TS models, which we attribute to the *uncontrolled integration of auxiliary modalities* that may introduce irrelevant information. Motivated by this observation, we explore various **constrained fusion** methods designed to control such integration and find that they consistently outperform naive fusion methods. Furthermore, we propose **Controlled Fusion Adapter** (**CFA**), a simple plug-in method that enables controlled cross-modal interactions without modifying the TS backbone, integrating *only relevant textual information aligned with TS dynamics*. CFA employs low-rank adapters to filter irrelevant textual information before fusing it into temporal representations. Across over 20K experiments, CFA ranks first among 11 compared methods while adding only 0.61% parameters. Code is available at `https://anonymous.4open.science/r/mmcfa-602D`.

1 INTRODUCTION

Time series (TS) forecasting is widely used across domains such as finance (Rezaei et al., 2021) and traffic (Cirstea et al., 2022). With the emergence of large language models (LLMs), multimodal TS forecasting has gained increasing attention (Jiang et al., 2025). Recent studies attempt to enhance TS forecasting by incorporating auxiliary modalities, including text (Park et al., 2025; Zhou et al., 2025), vision (Zhong et al., 2025; Ekambaram et al., 2020), and tabular (Chattopadhyay et al., 2024), under the assumption that such contextual information enhances the modeling of temporal dependencies.

Existing methods often adopt *naive fusion* strategies (e.g., simple addition or concatenation) (Li et al., 2025; Park et al., 2025) without carefully considering how modalities should interact, or rely on model-specific architectures (Liu et al., 2025; Yao et al., 2025; Nguyen et al., 2026) that are not easily integrated into unimodal TS models. Additionally, prior work shows that fusion does not consistently improve performance (Kim et al., 2024), due to the difficulty of alignment among modalities. Moreover, even when improvements are reported, we find that they often depend on the dataset or the model, indicating limitations of naive fusion.

In this paper, we conduct extensive experiments across diverse datasets and models (Table 3), evaluating fusion at the first, middle, and final layers with additive and concatenation operators. As shown in Figure 1, we find that *multimodal models with naive fusion often underperform unimodal models*, as both concatenation-based (red) and additive (blue) fusion frequently fall below the unimodal (gray) baseline, even under the best learning rate setting among 10 candidates. This observation motivates the need for improved fusion mechanisms, suggesting that more careful and *controlled fusion between TS and text is required*.

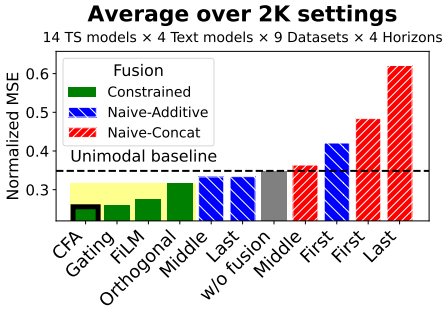

Figure 1: **Constrained** vs. **Naive** fusion.

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We attribute this phenomenon to the intrinsic nature of multimodal TS forecasting, where TS serve as the *primary* modality, while other modalities serve as *auxiliary* modalities that provide contextual guidance (Su et al., 2025; Zhong et al., 2025; Lin et al., 2026), *which may introduce irrelevant or conflicting information* (Zhu et al., 2025) that is misaligned with TS. Therefore, indiscriminate fusion can degrade forecasting performance, highlighting the necessity of **constrained fusion**, which we refer to as a fusion strategy that *incorporates auxiliary signals in a controlled manner* while preserving core temporal (TS) representations.

To this end, we explore various constrained fusion methods, which consistently outperform naive methods, as shown in Figure 1 (green). Furthermore, we propose **C**ontrolled **F**usion **A**dapter (**CFA**), a plug-in method that injects textual information via a residual connection constrained to a low-rank subspace, filtering irrelevant textual information while preserving temporal dynamics. CFA outperforms other constrained fusion methods and remains effective even when naive fusion degrades performance. The main contributions are:

- We show that *naive* multimodal fusion often underperforms unimodal setting and demonstrate that *constrained* fusion consistently improves over naive strategies across diverse datasets and models through extensive experiments.
- We propose CFA, a simple yet effective fusion method for multimodal TS forecasting, which injects auxiliary textual information into TS representations via a residual connection constrained to a low-rank subspace, enabling controlled integration without modifying the backbone. In contrast to prior works that rely on architecture-specific designs, our method is a *plug-in* module, making it applicable to *any unimodal TS model*.
- We conduct over 20K experiments across various settings (9 multimodal datasets, 4 forecasting horizons, 14 TS models, and 4 text models) with 10 fusion strategies, demonstrating the effectiveness of constrained fusion including CFA. Additionally, we provide detailed analyses explaining *why constrained fusion strategies yield superior performance* compared to naive fusion strategies.

2 Related Works

Multimodal TS forecasting models. Recent work integrates external modalities with TS to enrich forecasting with contextual information (Jin et al., 2024; Xue & Salim, 2024; Jiang et al., 2025). UniCast (Park et al., 2025) combines pretrained vision and text encoders with a frozen TS foundation model. Multi-Modal Forecaster (Kim et al., 2024) jointly models TS and text through shared embeddings. CAPTime (Yao et al., 2025) aligns TS representations with LLM-derived textual context within a probabilistic forecasting framework. BALM-TSF (Zhou et al., 2025) mitigates modality imbalance by aligning TS and textual embeddings before fusion. SpecTF (Nguyen et al., 2026) performs frequency-domain fusion by projecting textual embeddings into the spectral space and integrating them with TS components. Time-VLM (Zhong et al., 2025) leverages pretrained vision-language models to construct multimodal representations. TimeCMA (Liu et al., 2025) performs cross-modality alignment with dual branches. GPT4MTS (Jia et al., 2024) employs LLMs to generate textual prompts to guide forecasting. T3Time (Chowdhury et al., 2025) employs temporal, spectral, and prompt features with gating mechanism.

Table 1: **Text+TS fusion.** CFA is both plug-in to existing models and constrained fusion.

Approach	1) Plug-in	2) Constrained fusion
Architecture-specific	✗	—
Naive plug-in	✓	✗
CFA (Ours)	✓	✓

As shown in Table 1, these works either adopt naive fusion strategies or focus on designing architecture-specific models for multimodal forecasting, which are not generally applicable to existing unimodal TS models. While TaTS (Li et al., 2025) can be plugged into existing unimodal TS models, it adopts a naive first-layer additive fusion scheme included as a baseline in our experiments. Additionally, although ContextFormer (Chattopadhyay et al., 2024) can be applied to arbitrary TS encoders, its module accounts for over 75% of the total parameters due to cross-attention layers, limiting general applicability. Low-rank structure is also used elsewhere in multimodal learning, either to build *joint* representations from symmetrically treated modalities (Liu et al., 2018; Sahay et al., 2020; Shankar et al., 2022; Han et al., 2024) or to constrain *weight* updates for parameter-efficient adaptation (Hu et al., 2022; Nie et al., 2024; Palaskar et al., 2024). CFA differs on both counts: it treats TS as primary and text as an auxiliary signal to be filtered, and it constrains the

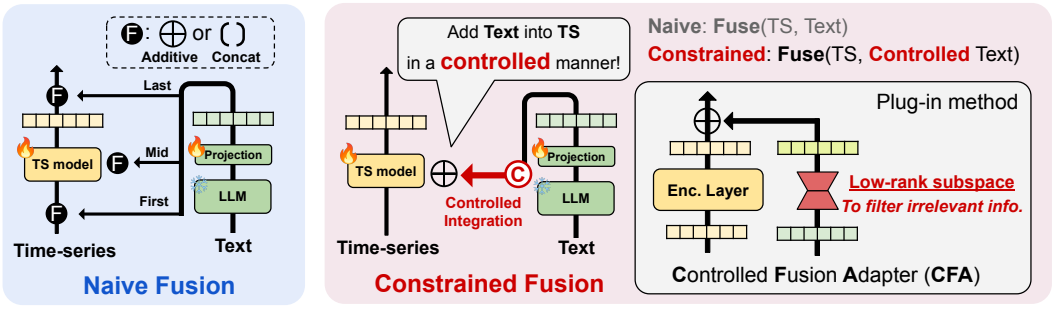


Figure 2: **Comparison of multimodal fusion (TS+Text) strategies.** (**Left**) *Naive fusion* applies simple additive or concatenation operators at first, middle, or last stages without considering modality relevance. (**Right**) *Constrained fusion* incorporates textual information in a controlled manner by considering its relevance to TS. *CFA* injects textual signals via a residual connection constrained to a low-rank subspace to filter irrelevant information.

injected cross-modal signal rather than the joint representation or the weights, leaving the backbone untouched. For an overview of unimodal TS forecasting models, see Appendix C.

3 Necessity of Constrained Fusion

In multimodal forecasting, a model predicts future values $\mathbf{y} = (\mathbf{x}_{L+1}, \ldots, \mathbf{x}_{L+H})$ given a lookback window $\mathbf{x} = (\mathbf{x}_1, \ldots, \mathbf{x}_L)$ and a paired text sequence $\mathbf{t} = (\mathbf{t}_1, \ldots, \mathbf{t}_L)$. Each $\mathbf{x}_i \in \mathbb{R}^C$ denotes observations at time step i, where L, H, and C represent the lookback length, forecast horizon, and number of channels. Each text $\mathbf{t}_i$ is encoded by a language model as $\mathbf{z}_{\text{Text},i} = g_{\text{Text}}(\mathbf{t}_i)$, forming a text embedding $\mathbf{Z}_{\text{Text}} = (\mathbf{z}_{\text{Text},1}, \ldots, \mathbf{z}_{\text{Text},L})$. Note that text is paired only with the lookback window and never with the horizon, so no information about $\mathbf{y}$ can enter through the text channel (Appendix G.1).

3.1 Naive Fusion

Naive fusion integrates textual information using a fusion operator (e.g., addition or concatenation), where the text embeddings produced by the text encoder are *directly* fused with TS embeddings. Fusion can be applied before the encoder (first fusion), within intermediate encoder layers (middle fusion), or after temporal encoding (last fusion), as shown in Algorithm 1. Many multimodal TS forecasting methods follow this approach (Jin et al., 2024; Kim et al., 2024; Li et al., 2025; Liu et al., 2024a), while others typically adopt architecture-specific designs to fuse different modalities (Chowdhury et al., 2025; Nguyen et al., 2026; Yao et al., 2025; Zhong et al., 2025), which are not applicable to existing TS models.

Algorithm 1 Multimodal TS forecasting.

Input: $\mathbf{X} = [\mathbf{X}_1, \ldots, \mathbf{X}_L]$, $\mathbf{T} = [\mathbf{T}_1, \ldots, \mathbf{T}_L]$
Output: $\hat{\mathbf{Y}} = [\hat{\mathbf{X}}_{L+1}, \ldots, \hat{\mathbf{X}}_{L+H}]$

$\mathbf{Z}_{\text{TS}} \leftarrow g_{\text{TS}}(\mathbf{X})$, $\mathbf{Z}_{\text{Text}} \leftarrow g_{\text{Text}}(\mathbf{T})$ // Input projection
$\mathbf{Z}_{\text{TS}} \leftarrow \mathcal{F}(\mathbf{Z}_{\text{TS}}, \mathbf{Z}_{\text{Text}})$ // First fusion
for m in encoder layers **do**
  $\mathbf{Z}_{\text{TS}} \leftarrow f(\mathbf{Z}_{\text{TS}})$
  $\mathbf{Z}_{\text{TS}} \leftarrow \mathcal{F}(\mathbf{Z}_{\text{TS}}, \mathbf{Z}_{\text{Text}})$ // Middle fusion
end for
$\mathbf{Z}_{\text{TS}} \leftarrow \mathcal{F}(\mathbf{Z}_{\text{TS}}, \mathbf{Z}_{\text{Text}})$ // Last fusion
$\hat{\mathbf{Y}} \leftarrow h(\mathbf{Z}_{\text{TS}})$ // Output projection

3.2 Constrained Fusion

In this paper, we argue that TS forecasting primarily relies on learning temporal representations, while auxiliary modalities provide contextual guidance *that may contain information irrelevant to TS*. However, naive fusion methods do not account for this misalignment, which may disrupt temporal representations and underperform a unimodal (TS-only) model. To investigate this effect, we explore various constrained fusion strategies (Details in Appendix K), which incorporate information from other modalities in a constrained manner while preserving temporal representations as:

- **1) Gating mechanism** determines the relevance of text information at each time step using a learned gate, allowing the model to utilize only the necessary textual information.

- **2) FiLM (Feature-wise Linear Modulation)**[1] (Perez et al., 2018) modulates the scale and bias of TS embeddings based on text embeddings, preserving temporal structure while adjusting feature representations.
- **3) Orthogonal fusion** projects text embeddings into the TS embedding space and injects only the orthogonal component, explicitly preserving temporal information without overwriting it.

Naive vs. Constrained fusion. As shown in Figure 1, these *constrained fusion strategies generally outperform naive fusion strategies* across various settings. Nonetheless, they can *still underperform unimodal baselines under certain settings* (Table 4). This motivates the need to more effectively filter irrelevant textual signals while preserving informative ones. Comparison of naive and constrained fusion is provided in Figure 2.

3.3 Controlled Fusion Adapter (CFA)

Based on these insights, we propose Controlled Fusion Adapter (**CFA**), a model-agnostic fusion method projecting text embeddings through a low-rank bottleneck and adding them to TS embeddings as residuals. Note that our goal is *not to develop a novel adapter* but to design a *controlled fusion formulation* that constrains the textual signal effectively. To implement this, we adopt a LoRA-style parameterization (Hu et al., 2022), enabling lightweight integration across TS backbones. Appendix D details how CFA differs from low-rank fusion and parameter-efficient adaptation. The low-rank bottleneck limits textual capacity and encourages retention of information useful for forecasting while filtering irrelevant information, as:

$$\mathbf{z}_{\text{Adapter},t} = \mathbf{W}_{\text{down}}\, \mathbf{z}_{\text{Text},t} \in \mathbb{R}^{D/r} \tag{1a}$$

$$\mathbf{z}'_{\text{Adapter},t} = \text{ReLU}(\text{LayerNorm}(\mathbf{z}_{\text{Adapter},t})) \tag{1b}$$

$$\mathbf{z}''_{\text{Adapter},t} = \mathbf{W}_{\text{up}}\, \mathbf{z}'_{\text{Adapter},t} \in \mathbb{R}^{D} \tag{1c}$$

$$\tilde{\mathbf{z}}_{\text{TS},t} = \mathbf{z}_{\text{TS},t} + \mathbf{z}''_{\text{Adapter},t}. \tag{1d}$$

Table 2: Constrained fusion methods.

Methods	
Gating	$\mathbf{z}_{\text{TS},t} + \mathbf{g}_t \odot \mathbf{z}_{\text{Text},t}$
FiLM	$\boldsymbol{\gamma}_t \odot \mathbf{z}_{\text{TS},t} + \boldsymbol{\beta}_t$
Orthogonal	$\mathbf{z}_{\text{TS},t} + \mathbf{z}^{\perp}_{\text{Text},t}$
CFA	$\mathbf{z}_{\text{TS},t} + \mathbf{W}_{\text{up}}\, \phi(\mathbf{W}_{\text{down}} \mathbf{z}_{\text{Text},t})$.

Here, $\tilde{\mathbf{z}}_{\text{TS},t}$ denotes the fused embedding at time step t, and the residual addition is applied at each encoder layer of any TS model. The bottleneck width D/r (D: embedding size) sets the parameter cost, with $r = 8$. Table 2 compares the four constrained fusion strategies, and Appendix P discusses robustness to the choice of r. Additionally, a theoretical perspective showing how the bottleneck constrains the textual signals to a low-dimensional subspace is provided in Appendix L.

Role of low-rank bottleneck. To understand the role of the bottleneck, we conduct a toy experiment examining how it affects fusion under 1) informative, 2) contradicting, and 3) irrelevant texts. The results show that *the low-rank projection suppresses misleading textual signals while preserving useful guidance*. Details are provided in Appendix J, with three complementary analyses:

- **(J.1) Performance comparison.** We compare forecasting performance w/ and w/o the low-rank bottleneck across matching, contradicting, and irrelevant text. The results show that the low-rank bottleneck consistently improves performance and provides the *largest gain with irrelevant text*.
- **(J.2) Representation analysis.** We measure the text-contribution ratio at the adapter to quantify how much textual signal survives the bottleneck. Matching text exhibits stronger contribution than contradicting text, indicating that the bottleneck *selectively preserves useful information*.
- **(J.3) TS visualization.** Forecast trajectories show that the bottleneck *prevents misleading predictions under contradicting text* while *preserving accurate forecasts when text is helpful*.

4 Experiments

Experimental settings. To evaluate the generality of the proposed method, we conduct experiments on 9 multimodal datasets (Liu et al., 2024a), 14 TS backbones, and 4 language models across 4 Hs, as shown in Table 3. In all experiments, only the TS model is trained while the text model

[1] FiLM (Perez et al., 2018) is different from FiLM (Zhou et al., 2022a), which is described in Appendix C.

Table 3: Experimental settings across 20K configurations (2K settings × 10 fusion methods).

Experimental settings ($[1] \times [2] \times [3] > 2K$)			
[1] Datasets			Agriculture, Climate, Economy, Energy, Environment, Public Health, Security, Social Good, Traffic (Liu et al., 2024a)
[2] Models	TS	Transformer	Nonstationary Transformer (Liu et al., 2022), PatchTST (Nie et al., 2023), iTransformer (Liu et al., 2024b), Crossformer (Zhang & Yan, 2023), FEDformer (Zhou et al., 2022b), Autoformer (Wu et al., 2021), Reformer (Kitaev et al., 2020), Informer (Zhou et al., 2021), Transformer (Vaswani et al., 2017)
		Linear/MLP	DLinear (Zeng et al., 2023), TiDE (Das et al., 2023), TSMixer (Chen et al., 2023)
		Others	Koopa (Liu et al., 2023), FiLM (Zhou et al., 2022a)
	Text		BERT (Devlin et al., 2019), GPT2 (Radford et al., 2019), Llama3 (Grattafiori et al., 2024), Doc2Vec (Le & Mikolov, 2014)
[3] Forecasting horizons (H)			[Daily]: {48, 96, 192, 336}. [Weekly]: {12, 24, 36, 48}. [Monthly]: {6, 8, 10, 12}.
Fusion methods (10)			
Naive		Additive	First (Li et al., 2025; Jia et al., 2024), Middle, Last (Liu et al., 2024a)
		Concat	First (Park et al., 2025; Kim et al., 2024; Jin et al., 2024), Middle, Last
Constrained			Orthogonal, FiLM (Perez et al., 2018), Gating (Zhong et al., 2025; Chowdhury et al., 2025), **CFA** (Ours)

remains frozen. Each setting is evaluated over 10 learning rates, reporting the best result. Following Time-MMD (Liu et al., 2024a), datasets are split into train, validation, and test sets with a ratio of 7:1:2. Performance is evaluated using MSE and MAE.

4.1 Multimodal Time Series Forecasting

Table 4 presents the forecasting performance (MSE) of multimodal fusion strategies across TS models and datasets using BERT (Devlin et al., 2019) as the language model. Due to space limitations, we report six TS models (Liu et al., 2022; Nie et al., 2023; Zeng et al., 2023; Das et al., 2023; Liu et al., 2023; Zhou et al., 2022a), selecting the two representative methods from each model category with the highest performance. Overall, *naive fusion* methods, whether additive or concatenation-based, frequently fail to outperform the unimodal baseline and even lead to severe degradation or divergence. In contrast, *constrained fusion* methods consistently yield more stable and better performance across models and domains. Notably, CFA achieves the best performance, indicating that controlled integration of textual information is crucial for robust multimodal TS forecasting. Brief and full results for all TS/text models are presented in Section 4.2 and Appendix T, respectively. Additionally, comparisons with architecture-specific methods are shown in Appendix S.

4.2 Performance with Various Settings

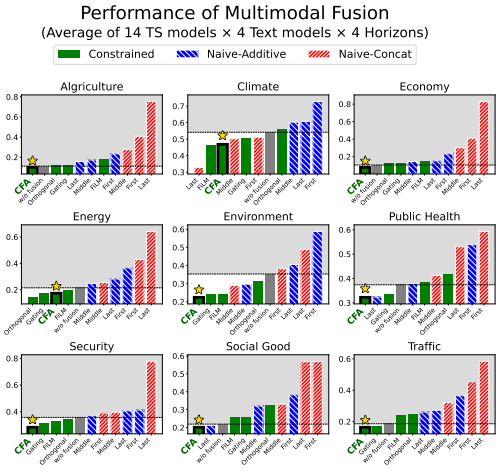
In this section, we evaluate the proposed method across diverse **1) datasets**, **2) TS backbones**, and **3) text encoders** to verify its general effectiveness. To account for scale differences across datasets, we report normalized MSE for each of the 10 fusion (6 naive & 4 constrained fusion) strategies.

1) Various datasets (Figure 3a). We conduct experiments on 9 real-world multimodal datasets (Liu et al., 2024a) for TS forecasting. Across datasets, constrained fusion strategies (green) generally outperform the additive (blue) and concatenation-based (red) fusion. While many fusion methods exhibit dataset-dependent behavior (i.e., improving on some datasets and underperforming on others), CFA consistently outperforms the unimodal model on all datasets and ranks first on 7 of the 9 datasets.

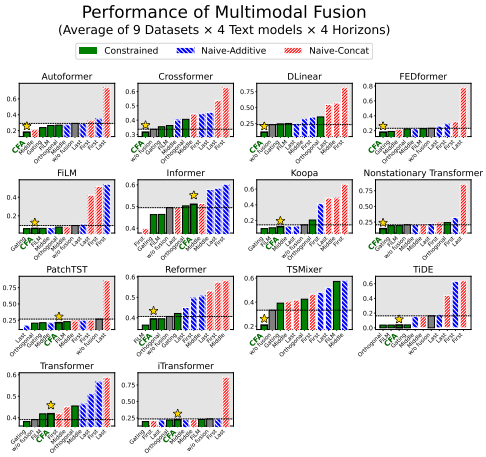
2) Various TS models (Figure 3b). We evaluate the effectiveness of our method across diverse TS backbones (e.g., Transformer-based, linear/MLP-based). Similar to the dataset-level analysis, constrained fusion strategies (green) generally outperform the additive (blue) and concatenation-based (red) approaches. Specifically, CFA improves over the unimodal baseline on 13 out of 14 backbones, with the exception of Transformer (Vaswani et al., 2017). We attribute this to the fact that the standard Transformer exhibits substantially lower performance than other TS backbones, indicating a limitation of the backbone itself rather than the fusion strategy. For Transformer variants specifically designed for TS forecasting (Liu et al., 2022; 2024b; Zhang & Yan, 2023), CFA consistently yields improvements over unimodal models.

Table 4: **Performance across multimodal fusion strategies.** While naive fusions often underperform the unimodal baseline, *constrained* fusions consistently perform better, with our *CFA showing robust improvements across diverse settings*. **Red**/blue denotes improvements/degradations over the unimodal model, averaged across four Hs. Divergence (*Div.**) indicates cases where the MSE exceeds that of the unimodal baseline by more than $10\times$.

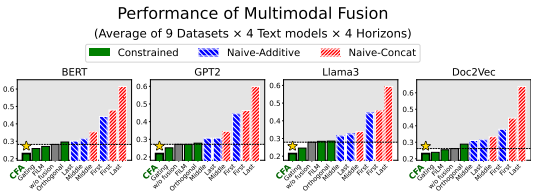
TS Model	Dataset	Unimodal (w/o text)	Naive						Constrained			
			Additive			Concat						
			First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	CFA
(1) ***Transformer***-based methods												
Nonstationary Transformer	Agriculture	0.084	0.089	**0.082**	**0.079**	0.090	0.084	0.892	**0.084**	0.085	0.085	**0.082**
	Climate	1.248	1.287	**1.229**	**1.210**	**1.215**	**1.230**	**1.153**	1.264	**1.208**	**1.232**	**1.170**
	Economy	0.019	0.020	0.020	0.020	0.020	0.019	*Div.**	0.019	0.019	0.020	**0.019**
	Energy	0.247	0.268	0.256	0.257	0.252	0.252	0.572	**0.240**	**0.243**	**0.243**	**0.244**
	Environment	0.437	0.478	0.447	0.437	0.447	0.453	0.461	0.441	**0.436**	0.447	0.442
	Public Health	1.210	1.224	**1.141**	**1.176**	1.271	1.240	1.465	1.235	1.285	**1.153**	**1.086**
	Security	106.4	106.4	107.8	107.4	**106.1**	107.0	121.5	**105.7**	**105.3**	**106.1**	**105.8**
	Social Good	0.942	**0.940**	**0.918**	**0.893**	1.000	**0.910**	2.362	0.993	**0.932**	**0.925**	**0.910**
	Traffic	0.199	0.201	0.201	0.210	0.201	**0.194**	0.419	0.202	0.201	**0.198**	**0.197**
	Win rate (vs. Unimodal) (%)		11.1	44.4	44.4	22.2	33.3	11.1	33.3	55.6	66.7	**88.9**
PatchTST	Agriculture	0.092	0.092	0.093	**0.088**	0.092	0.093	0.547	0.093	0.092	0.093	**0.091**
	Climate	1.259	**1.254**	**1.243**	1.260	**1.254**	1.259	**1.169**	**1.243**	1.265	**1.236**	**1.252**
	Economy	0.017	0.017	**0.017**	0.019	0.017	0.017	*Div.**	0.017	0.018	0.018	**0.017**
	Energy	0.264	0.265	**0.263**	**0.252**	0.265	**0.258**	0.723	**0.262**	**0.257**	**0.260**	**0.263**
	Environment	0.502	0.502	**0.447**	**0.492**	0.502	**0.471**	0.583	**0.456**	**0.451**	**0.455**	**0.442**
	Public Health	1.390	**1.388**	1.413	**1.194**	**1.388**	1.418	1.472	1.400	**1.384**	1.394	**1.390**
	Security	109.5	**108.8**	**106.7**	**108.0**	**108.8**	**107.5**	128.7	**106.5**	**108.5**	**108.0**	**109.1**
	Social Good	0.955	0.966	**0.943**	**0.890**	0.966	**0.948**	2.195	**0.943**	**0.939**	**0.954**	**0.920**
	Traffic	0.199	**0.198**	0.201	0.210	**0.198**	**0.197**	0.744	**0.198**	**0.195**	**0.195**	0.201
	Win rate (vs. Unimodal) (%)		44.4	66.7	66.7	44.4	55.6	11.1	66.7	66.7	66.7	**88.9**
(2) ***Linear/MLP***-based methods												
DLinear	Agriculture	0.205	**0.183**	**0.188**	**0.191**	0.651	0.746	0.609	**0.169**	0.259	**0.188**	**0.124**
	Climate	1.225	1.324	1.309	1.283	1.227	**1.167**	**1.159**	1.312	**1.090**	1.312	**1.098**
	Economy	0.129	**0.116**	**0.124**	**0.126**	*Div.**	*Div.**	*Div.**	**0.110**	0.248	**0.125**	**0.040**
	Energy	0.263	0.326	0.314	0.291	0.670	0.382	0.368	0.298	0.313	0.299	**0.243**
	Environment	0.545	**0.491**	**0.489**	**0.479**	**0.528**	**0.501**	**0.497**	0.549	**0.500**	**0.485**	0.546
	Public Health	1.554	1.604	1.569	**1.549**	1.790	1.637	1.570	1.736	1.682	**1.517**	**1.530**
	Security	109.0	110.7	109.8	109.2	142.6	137.6	136.1	110.1	**108.6**	109.3	**108.8**
	Social Good	0.934	1.096	1.069	1.068	1.928	1.587	1.491	1.037	0.981	1.026	**0.904**
	Traffic	0.276	0.334	0.358	0.343	0.841	0.883	0.757	0.301	0.333	0.340	**0.233**
	Win rate (vs. Unimodal) (%)		33.3	33.3	44.4	11.1	22.2	22.2	22.2	33.3	44.4	**88.9**
TiDE	Agriculture	0.108	*Div.**	**0.107**	**0.099**	*Div.**	**0.107**	0.824	**0.096**	**0.096**	**0.095**	**0.095**
	Climate	1.469	*Div.**	1.487	1.506	2.954	1.505	**1.231**	**1.261**	**1.267**	**1.255**	**1.264**
	Economy	0.035	*Div.**	**0.034**	0.042	*Div.**	0.038	*Div.**	**0.017**	**0.017**	**0.018**	**0.017**
	Energy	0.287	*Div.**	0.290	0.291	*Div.**	0.288	0.768	**0.256**	**0.262**	**0.259**	**0.260**
	Environment	0.534	*Div.**	0.535	**0.515**	*Div.**	**0.534**	0.555	**0.534**	**0.533**	**0.533**	**0.533**
	Public Health	1.568	*Div.**	**1.561**	1.643	*Div.**	1.588	1.752	**1.459**	**1.476**	**1.476**	**1.463**
	Security	138.3	143.9	**135.4**	**134.5**	140.1	**132.2**	146.1	**109.7**	**109.7**	**111.7**	**110.1**
	Social Good	1.185	*Div.**	**1.083**	**1.143**	*Div.**	**1.115**	2.125	**1.004**	**1.025**	**1.016**	**1.001**
	Traffic	0.295	*Div.**	**0.279**	0.325	*Div.**	0.302	0.472	**0.245**	**0.247**	**0.245**	**0.244**
	Win rate (vs. Unimodal) (%)		0.0	66.7	44.4	0.0	44.4	11.1	**100.0**	**100.0**	**100.0**	**100.0**
(3) ***Others***												
Koopa	Agriculture	0.091	**0.084**	**0.084**	**0.084**	*Div.**	0.699	0.699	0.092	0.123	**0.085**	**0.090**
	Climate	1.249	5.219	1.257	1.257	2.602	**1.147**	**1.147**	1.284	**1.088**	1.252	**1.248**
	Economy	0.018	0.028	0.024	0.024	*Div.**	*Div.**	*Div.**	0.028	0.051	0.021	**0.018**
	Energy	0.253	*Div.**	**0.252**	**0.252**	*Div.**	0.534	0.534	0.270	0.262	**0.247**	**0.253**
	Environment	0.526	*Div.**	**0.497**	**0.497**	*Div.**	**0.470**	**0.470**	0.530	**0.483**	**0.496**	0.527
	Public Health	1.442	*Div.**	**1.184**	**1.184**	*Div.**	**1.381**	**1.381**	1.637	**1.367**	**1.176**	**1.439**
	Security	108.5	**108.2**	**107.6**	**107.6**	130.1	131.6	131.6	110.1	111.8	**106.6**	**107.0**
	Social Good	0.964	0.996	0.976	0.976	2.180	2.097	2.097	0.993	**0.841**	**0.918**	**0.959**
	Traffic	0.233	0.256	0.244	0.244	0.431	0.366	0.366	0.249	0.239	0.242	**0.219**
	Win rate (vs. Unimodal) (%)		22.2	55.6	55.6	0.0	33.3	33.3	0.0	44.4	66.7	**88.9**
FiLM	Agriculture	0.098	*Div.**	**0.095**	**0.092**	*Div.**	0.099	0.896	**0.096**	**0.097**	**0.095**	**0.094**
	Climate	1.286	8.799	**1.286**	**1.274**	6.623	1.291	**1.168**	**1.280**	**1.282**	**1.274**	**1.264**
	Economy	0.018	*Div.**	0.022	0.029	*Div.**	0.022	*Div.**	0.018	**0.018**	0.018	**0.018**
	Energy	0.271	*Div.**	0.285	0.294	0.807	0.307	0.737	**0.260**	**0.268**	0.275	**0.259**
	Environment	0.534	*Div.**	**0.504**	**0.512**	*Div.**	**0.492**	0.565	0.535	**0.509**	**0.493**	**0.532**
	Public Health	1.501	*Div.**	1.531	1.615	2.589	1.646	1.726	1.505	1.529	**1.493**	**1.490**
	Security	118.5	122.3	**106.7**	**114.7**	*Div.**	**107.0**	144.7	**108.8**	**107.4**	**107.2**	**110.0**
	Social Good	1.057	*Div.**	**0.993**	**1.032**	*Div.**	**1.048**	2.289	**1.013**	**1.019**	**0.990**	**1.018**
	Traffic	0.230	0.587	0.231	0.239	1.064	0.237	0.698	0.256	0.233	0.238	0.234
	Win rate (vs. Unimodal) (%)		0.0	55.6	55.6	0.0	33.3	11.1	55.6	77.8	66.7	**88.9**



(a) Performance by **Dataset**.



(b) Performance by **TS models**.



(c) Performance by **Text models**.

Method	Normalized MSE
Concat - F/M/L	0.484/0.364/0.621
Additive - F/M/L	0.421/0.333/0.334
w/o fusion	0.349
Orth./FiLM/Gating	0.317/0.275/0.261
CFA (Ours)	**0.256**

(d) Avg performance by **Dataset/Models**.

Figure 3: **Performance across diverse settings.** (a), (b), and (c) show the performance (normalized MSE) by **Dataset**, **TS model**, and **Text model**, respectively. (d) shows the overall average performance across all settings. CFA (⋆) achieves the lowest MSE in most settings.

3) Various text models (Figure 3c). To verify robustness to text encoders, we compare four text models, including three language-model encoders (Devlin et al., 2019; Radford et al., 2019; Grattafiori et al., 2024) and Doc2Vec (Le & Mikolov, 2014) to account for scenarios where LLM deployment is restricted. Consistent with previous observations, constrained fusion strategies (green) outperform additive (blue) and concatenation-based (red) methods, with CFA achieving the best performance.

4) Overall comparison (Table 3d). Table 3d reports the average normalized MSE across more than 2K settings (9 datasets × 14 TS models × 4 text models × 4 Hs) with 10 fusion methods. Among naive fusion strategies, only additive fusion at the middle or last layer improves over the unimodal baseline, whereas other naive approaches fail to do so. This highlights the necessity of constrained fusion for consistent performance gains. Furthermore, CFA achieves the best performance, confirming its superiority over various fusion strategies. Note that we tune each setting over 10 learning rates and compare the best performance to ensure that gains or losses are not due to optimization. Across 3 seeds, CFA improves over each tested baseline with $p < 0.01$ under a paired Wilcoxon test (Appendix Q).

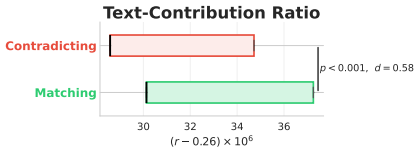
5 Analysis

In this section, we analyze *how and why the proposed method operates effectively* from ten perspectives, using BERT as the text model.

1) Performance with irrelevant text (Figure 5). To assess the effect of multimodal fusion, we conduct an *irrelevant text* experiment, where we replace the text aligned with each TS by text sampled from entirely different datasets. For instance, when evaluating on the Agriculture dataset, we randomly sample text from the remaining eight datasets, including Economy and Climate. This design examines how each fusion strategy responds when irrelevant textual information is injected. Appendix G.4 details the construction and why it is a robustness diagnostic, not our main claim.

Text type	w/o bottleneck	w/ bottleneck	Improv. (%)
Matching	0.1683	**0.1477**	+12.19
Contradicting	0.1635	**0.1560**	+4.59
Irrelevant	0.1851	**0.1480**	+20.04

(a) Per-type MSE: w/ vs. w/o low-rank bottleneck.



(b) Text-contribution ratio by text type.

Figure 4: **Experiment on low-rank bottleneck.** (a) CFA w/ bottleneck consistently outperforms w/o bottleneck across all text types, with the largest gain for irrelevant text. (b) Text-contribution ratio shows that matching text is injected more strongly than contradicting text.

A robust fusion strategy is expected to ignore unrelated information and rely on TS representations, so that its performance does not degrade much compared to the unimodal setting. As shown in Figure 5, CFA exhibits performance most similar to the unimodal model and shows the smallest degradation. In addition, constrained fusion strategies except Orthogonal effectively filter out unnecessary information. These results confirm that CFA incorporates relevant signals while remaining robust to irrelevant inputs.

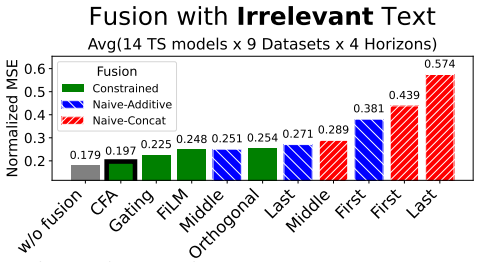


Figure 5: Experiment on **Irrelevant** text.

2) Effect of low-rank bottleneck (Figure 4). To analyze the filtering behavior of CFA's low-rank adapter, we conduct a controlled toy experiment on a synthetic dataset containing three text types: **matching** (reflecting the TS trend), **contradicting** (opposing the TS trend), and **irrelevant** (topically unrelated). We compare CFA w/ and w/o the bottleneck, with details in Appendix J.

Table 4a shows that the bottleneck consistently reduces MSE across all text types. The largest improvement occurs for irrelevant text, indicating that *the bottleneck suppresses uninformative texts*. Without the bottleneck, contradicting text yields *lower* MSE than matching text, suggesting that all text is treated as undifferentiated noise. With the bottleneck, the expected ordering appears, where matching text yields the lowest MSE, followed by irrelevant text and contradicting text.

Figure 4b reports the text-contribution ratio (Appendix J.2) measured at the adapter output. Matching text produces a higher mean ratio than contradicting text with strong statistical significance ($p<0.001$, Cohen's $d=0.58$). This indicates that CFA *injects helpful text more strongly while suppressing conflicting signals*. Forecast trajectories are visualized in Appendix J.3.

3) Temporal attribution analysis (Figure 6). Under the same experimental setting as **Analysis 5)**, we further analyze the importance scores that quantify *how much each input TS step contributes to the prediction*. Specifically, we compute a gradient $\times$ input attribution with respect to the encoder input and aggregate over channels to obtain one importance value per time step. As shown in Figure 6, CFA assigns a different importance distribution over input TS steps compared to w/o fusion and other methods, indicating that textual information influences which temporal regions are referenced for prediction. See Appendix M for details on the computation of temporal attribution.

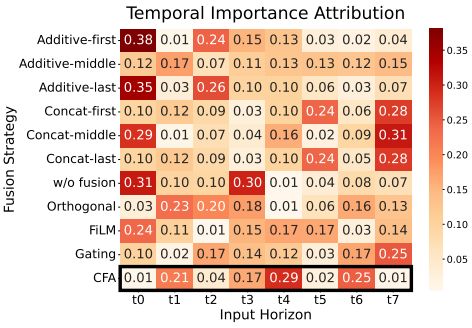


Figure 6: Temporal importance across input.

4) Efficiency analysis (Table 5). To demonstrate the efficiency of CFA, we compare the average number of training parameters and FLOPs across 10 fusion methods, aggregated over 14 TS backbones and 9 datasets under prediction lengths of 8, 36, and 96 for monthly, weekly, and daily frequencies. Gating, the closest competitor in accuracy, adds 28.62% parameters, while most other designs add marginal overhead. Notably, CFA increases parameters by only 0.61% and FLOPs by 0.04% relative to the unimodal model, indicating efficiency comparable to the unimodal setting.

Table 5: **Efficiency analysis of fusion strategies.** The table shows the average training parameters and FLOPs, where CFA achieves negligible overhead compared to the unimodal baseline.

Average	Unimodal (w/o text)	Naive						Constrained			
		Additive			Concat						
		First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
# Params. (1e+06)	9.382	9.384 + 0.02%	9.408 + 0.28%	9.384 + 0.02%	9.384 + 0.02%	10.539 + 12.33%	9.384 + 0.02%	9.403 + 0.23%	9.423 + 0.46%	12.067 + 28.62%	**9.439 + 0.61%**
FLOPs (1e+08)	1.436	1.436 + 0.00%	1.436 + 0.02%	1.436 + 0.00%	1.436 + 0.00%	1.616 + 12.53%	1.436 + 0.00%	1.436 + 0.02%	1.436 + 0.03%	1.885 + 31.26%	**1.436 + 0.04%**

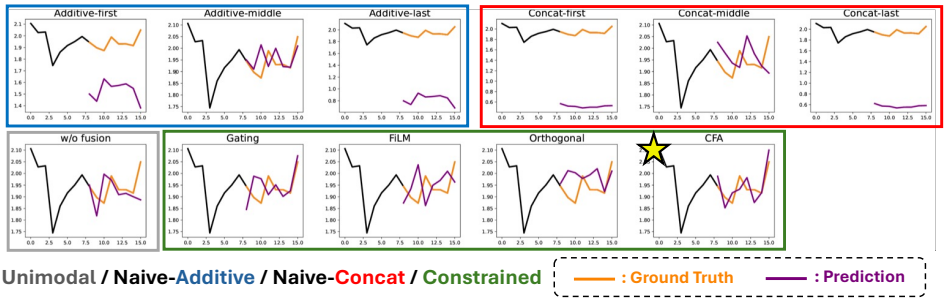


Figure 7: **Visualization of TS forecasting.** Although the unimodal model captures the initial pattern, it fails to model the upward trend, whereas CFA captures the rise in the later horizon.

5) Visualization of TS forecasting (Figure 7). We visualize forecasting results on Agriculture (Liu et al., 2024a) using TiDE (Das et al., 2023) ($L = H = 8$). The unimodal model captures the initial pattern but misses the subsequent upward trend, whereas CFA captures the late-stage rise. Several naive strategies even underperform the unimodal baseline.

6) Representation similarity (Appendix N). We compute *cosine similarity between TS-only and TS+Text representations* and observe that the best performance does not correspond to the largest representation shift, highlighting that effective fusion requires constrained modification rather than large deviation from the unimodal representation.

7) Information analysis (Appendix O). We compute the rank correlation between MAE and effective rank across diverse settings and find that methods with higher effective rank tend to achieve lower MAE, suggesting that models with more distributed representations forecast more accurately.

8) Misalignment vs. noise (Appendix G.3). Failures of naive fusion are often attributed to noisy text, but two failure modes are distinct. *Contradicting* text is topically relevant yet disagrees with the series, whereas *irrelevant* text carries no signal. The bottleneck helps in both cases, most on irrelevant text and least on contradicting text, since a misaligned signal is harder to separate from a useful one.

9) Statistical significance (Appendix Q). Because absolute errors differ by orders of magnitude across datasets, we also compare the 11 methods by their per-setting ranks over 2016 settings. A Friedman test rejects equivalence, and a Nemenyi post-hoc test places CFA first with a significant margin over every alternative. The unimodal baseline outranks all six naive variants.

10) Fusion on unimodal TS datasets (Appendix R). We further ask whether constrained fusion is needed when a benchmark provides no text at all. Using ETT as an example, we attach a text channel derived only from past values, so that the auxiliary signal is weak by construction. Even here, naive fusion fails to beat the unimodal model, while only CFA improves on it in both MSE and MAE.

6 Conclusion

In this paper, we show that naive fusion often underperforms unimodal baselines, suggesting that indiscriminate cross-modal fusion fails to preserve temporal representations. Constrained fusion instead improves performance by filtering irrelevant auxiliary signals while preserving those representations. We propose CFA, a constrained fusion method that suppresses irrelevant text in a low-rank subspace, and experiments across datasets and backbones validate its effectiveness. Limitations, including our focus on text paired with TS, are discussed in Appendix B.

AI USE STATEMENT

We used generative AI tools as writing and coding assistants. In the *required-disclosure* category, we used them to help select and implement the scripts for the standard statistical tests we report, which are computed from experimental results we had already obtained, and to reformat raw outputs into the aggregated tables. We also used them to check the reported tables for arithmetic consistency, and to help draft passages that interpret results we had already obtained, including the summary of claims and anticipated questions in Appendix A; every such passage was checked by us against the original results. We did not use them to generate synthetic datasets, to develop the theoretical models, to formulate mathematical claims, to write the proofs, to propose the hypotheses, to design the experiments, or to implement the proposed method. The remaining required-disclosure tasks, such as translation and qualitative data analysis, are not applicable to this work. In the *recommended-disclosure* category, we used them to copy-edit the manuscript, to draft descriptive passages that we then revised, to format tables and references, and to search for related literature. The research contributions of this paper are our own, and we have reviewed and verified all AI-assisted work. We take responsibility for the final content of this work, including any text, claims, and artifacts produced with the aid of generative AI.

ETHICS STATEMENT

This paper studies multimodal time series forecasting and proposes CFA, a plug-in method for constrained cross-modal interaction. All experiments use publicly available benchmark datasets that contain no personally identifiable information and no human subjects, and are used in accordance with their licenses. The impact of this work is primarily methodological. We note that incorrect or unvalidated deployment of multimodal forecasting systems may still lead to unreliable predictions, so careful evaluation is required before use in high-stakes environments. The authors have read and adhere to the ICLR Code of Ethics.

REPRODUCIBILITY STATEMENT

We have made the following efforts to ensure that all results in this paper can be reproduced. The full experimental setup is described in Section 4 and detailed in Appendix H, covering datasets and splits, forecasting horizons, text encoders, the training protocol, and the evaluation metrics. The complete hyperparameter grids used for every backbone and every fusion method are listed in Appendix I. Descriptions of all datasets, including their sources, preprocessing steps and text fields, are given in Appendix F, and descriptions of every TS backbone and text encoder we evaluate are given in Appendix E. Precise definitions of all constrained fusion variants (gating, FiLM, orthogonal fusion) and of the proposed Controlled Fusion Adapter, together with their exact formulations, are provided in Appendix K, and the assumptions and the complete derivation supporting our theoretical discussion are given in Appendix L. The full, non-aggregated results of the main experiments are reported in Appendix T. An anonymized implementation that reproduces all reported experiments, including the data preprocessing scripts, the training and evaluation entry points, and the configuration files for every reported setting, is available at `https://anonymous.4open.science/r/mmcfa-602D` and is also submitted as supplementary material. Appendix A maps each claim of the paper to the experiment that supports it.

REFERENCES

Sameep Chattopadhyay, Pulkit Paliwal, Sai Shankar Narasimhan, Shubhankar Agarwal, and Sandeep P Chinchali. Context matters: Leveraging contextual features for time series forecasting. *arXiv preprint arXiv:2410.12672*, 2024.

Si-An Chen, Chun-Liang Li, Nate Yoder, Sercan O Arik, and Tomas Pfister. TSMixer: An all-MLP architecture for time series forecasting. *TMLR*, 2023.

Abdul Monaf Chowdhury, Rabeya Akter, and Safaeid Hossain Arib. T3Time: Tri-modal time series forecasting via adaptive multi-head alignment and residual fusion. *arXiv preprint arXiv:2508.04251*, 2025.

Razvan-Gabriel Cirstea, Bin Yang, Chenjuan Guo, Tung Kieu, and Shirui Pan. Towards spatio-temporal aware traffic time series forecasting. In *2022 IEEE 38th International Conference on Data Engineering (ICDE)*, pp. 2900–2913. IEEE, 2022.

Abhimanyu Das, Weihao Kong, Andrew B. Leach, Shaan Mathur, Rajat Sen, and Rose Yu. Long-term forecasting with TiDE: Time-series dense encoder. *TMLR*, 2023.

Janez Demšar. Statistical comparisons of classifiers over multiple data sets. *Journal of Machine Learning Research*, 7:1–30, 2006.

Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: Pre-training of deep bidirectional transformers for language understanding. In *NAACL*, 2019.

Vijay Ekambaram, Kushagra Manglik, Sumanta Mukherjee, Surya Shravan Kumar Sajja, Satyam Dwivedi, and Vikas Raykar. Attention based multi-modal new product sales time-series forecasting. In *Proceedings of the 26th ACM SIGKDD international conference on knowledge discovery & data mining*, pp. 3110–3118, 2020.

Aaron Grattafiori, Abhimanyu Dubey, Abhinav Jauhri, Abhinav Pandey, Abhishek Kadian, Ahmad Al-Dahle, Aiesha Letman, Akhil Mathur, Alan Schelten, Alex Vaughan, et al. The Llama 3 herd of models. *arXiv preprint arXiv:2407.21783*, 2024.

Xing Han, Huy Nguyen, Carl Harris, Nhat Ho, and Suchi Saria. FuseMoE: Mixture-of-experts transformers for fleximodal fusion. In *NeurIPS*, 2024.

Edward J Hu, Yelong Shen, Phillip Wallis, Zeyuan Allen-Zhu, Yuanzhi Li, Shean Wang, Lu Wang, and Weizhu Chen. LoRA: Low-rank adaptation of large language models. In *ICLR*, 2022.

Furong Jia, Kevin Wang, Yixiang Zheng, Defu Cao, and Yan Liu. GPT4MTS: Prompt-based large language model for multimodal time-series forecasting. In *AAAI*, 2024.

Yushan Jiang, Kanghui Ning, Zijie Pan, Xuyang Shen, Jingchao Ni, Wenchao Yu, Anderson Schneider, Haifeng Chen, Yuriy Nevmyvaka, and Dongjin Song. Multi-modal time series analysis: A tutorial and survey. In *Proceedings of the 31st ACM SIGKDD Conference on Knowledge Discovery and Data Mining V. 2*, pp. 6043–6053, 2025.

Ming Jin, Shiyu Wang, Lintao Ma, Zhixuan Chu, James Y Zhang, Xiaoming Shi, Pin-Yu Chen, Yuxuan Liang, Yuan-Fang Li, Shirui Pan, et al. Time-LLM: Time series forecasting by reprogramming large language models. In *ICLR*, 2024.

Kai Kim, Howard Tsai, Rajat Sen, Abhimanyu Das, Zihao Zhou, Abhishek Tanpure, Mathew Luo, and Rose Yu. Multi-modal forecaster: Jointly predicting time series and textual data. arXiv:2411.06735, 2024. Preprint.

Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

Nikita Kitaev, Łukasz Kaiser, and Anselm Levskaya. Reformer: The efficient transformer. *arXiv preprint arXiv:2001.04451*, 2020.

Quoc V. Le and Tomas Mikolov. Distributed representations of sentences and documents. In *ICML*, 2014. URL `https://proceedings.mlr.press/v32/le14.html`.

Zihao Li, Xiao Lin, Zhining Liu, Jiaru Zou, Ziwei Wu, Lecheng Zheng, Dongqi Fu, Yada Zhu, Hendrik Hamann, Hanghang Tong, et al. Language in the flow of time: Time-series-paired texts weaved into a unified temporal narrative. *arXiv preprint arXiv:2502.08942*, 2025.

Jiafeng Lin, Yuxuan Wang, Huakun Luo, Jianmin Wang, and Zhongyi Pei. TiMi: Empower time series transformers with multimodal mixture of experts. *arXiv preprint arXiv:2602.21693*, 2026.

Chenxi Liu, Qianxiong Xu, Hao Miao, Sun Yang, Lingzheng Zhang, Cheng Long, Ziyue Li, and Rui Zhao. TimeCMA: Towards LLM-empowered multivariate time series forecasting via cross-modality alignment. In *AAAI*, 2025.

Haoxin Liu, Shangqing Xu, Zhiyuan Zhao, Lingkai Kong, Harshavardhan Kamarthi, Aditya B. Sasanur, Megha Sharma, Jiaming Cui, Qingsong Wen, Chao Zhang, et al. Time-MMD: Multi-domain multimodal dataset for time series analysis. *Advances in Neural Information Processing Systems*, 37:77888–77933, 2024a.

Yong Liu, Haixu Wu, Jianmin Wang, and Mingsheng Long. Non-stationary transformers: Exploring the stationarity in time series forecasting. In *Advances in Neural Information Processing Systems (NeurIPS)*, 2022.

Yong Liu, Chenyu Li, Jianmin Wang, and Mingsheng Long. Koopa: Learning non-stationary time series dynamics with Koopman predictors. *Advances in neural information processing systems*, 36: 12271–12290, 2023.

Yong Liu, Tengge Hu, Haoran Zhang, Haixu Wu, Shiyu Wang, Lintao Ma, and Mingsheng Long. iTransformer: Inverted transformers are effective for time series forecasting. In *ICLR*, 2024b.

Zhun Liu, Ying Shen, Varun Bharadhwaj Lakshminarasimhan, Paul Pu Liang, AmirAli Bagher Zadeh, and Louis-Philippe Morency. Efficient low-rank multimodal fusion with modality-specific factors. In *ACL*, pp. 2247–2256, 2018.

Huu Hiep Nguyen, Minh Hoang Nguyen, Dung Nguyen, and Hung Le. Spectral text fusion: A frequency-aware approach to multimodal time-series forecasting. arXiv:2602.01588, 2026. Preprint.

Tong Nie, Yuewen Mei, Guoyang Qin, Jian Sun, and Wei Ma. Channel-aware low-rank adaptation in time series forecasting. In *CIKM*, pp. 3959–3963, 2024.

Yuqi Nie, Nam H. Nguyen, Phanwadee Sinthong, and Jayant Kalagnanam. A time series is worth 64 words: Long-term forecasting with transformers. In *ICLR*, 2023.

Shruti Palaskar, Oggi Rudovic, Sameer Dharur, Florian Pesce, Gautam Krishna, Aman Sivaraman, Jack Berkowitz, Ahmed Hussen Abdelaziz, Saurabh Adya, and Ahmed Tewfik. Multimodal large language models with fusion low rank adaptation for device directed speech detection. In *Interspeech*, 2024.

Sehyuk Park, Soyeon Caren Han, and Eduard Hovy. UniCast: A unified framework for instance-conditioned multimodal time-series forecasting. arXiv:2508.11954, 2025. Preprint.

Ethan Perez, Florian Strub, Harm De Vries, Vincent Dumoulin, and Aaron Courville. FiLM: Visual reasoning with a general conditioning layer. In *AAAI*, 2018.

Alec Radford, Jeff Wu, Rewon Child, David Luan, Dario Amodei, and Ilya Sutskever. Language models are unsupervised multitask learners. *OpenAI*, 2019. URL `https://cdn.openai.com/better-language-models/language_models_are_unsupervised_multitask_learners.pdf`. Technical report.

Hadi Rezaei, Hamidreza Faaljou, and Gholamreza Mansourfar. Stock price prediction using deep learning and frequency decomposition. *Expert Systems with Applications*, 169:114332, 2021.

Saurav Sahay, Eda Okur, Shachi H Kumar, and Lama Nachman. Low rank fusion based transformers for multimodal sequences. In *Second Grand-Challenge and Workshop on Multimodal Language (Challenge-HML)*, 2020.

Shiv Shankar, Laure Thompson, and Madalina Fiterau. Progressive fusion for multimodal integration. *arXiv preprint arXiv:2209.00302*, 2022.

Chen Su, Yuanhe Tian, and Yan Song. Multimodal conditioned diffusive time series forecasting. *arXiv preprint arXiv:2504.19669*, 2025.

Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *NeurIPS*, 2017.

Chengsen Wang, Qi Qi, Jingyu Wang, Haifeng Sun, Zirui Zhuang, Jinming Wu, Lei Zhang, and Jianxin Liao. ChatTime: A unified multimodal time series foundation model bridging numerical and textual data. In *AAAI*, 2025.

Yuxuan Wang, Haixu Wu, Jiaxiang Dong, Guo Qin, Haoran Zhang, Yong Liu, Yunzhong Qiu, Jianmin Wang, and Mingsheng Long. TimeXer: Empowering transformers for time series forecasting with exogenous variables. *Advances in Neural Information Processing Systems*, 37:469–498, 2024.

Haixu Wu, Jiehui Xu, Jianmin Wang, and Mingsheng Long. Autoformer: Decomposition transformers with auto-correlation for long-term series forecasting. In *NeurIPS*, 2021.

Hao Xue and Flora D Salim. PromptCast: A new prompt-based learning paradigm for time series forecasting. *IEEE Transactions on Knowledge and Data Engineering*, 36(11):6851–6864, 2024.

Yueyang Yao, Jiajun Li, Xingyuan Dai, MengMeng Zhang, Xiaoyan Gong, Fei-Yue Wang, and Yisheng Lv. Context-aware probabilistic modeling with LLM for multimodal time series forecasting. arXiv:2505.10774, 2025. Preprint.

Kun Yi, Qi Zhang, Wei Fan, Shoujin Wang, Pengyang Wang, Hui He, Defu Lian, Ning An, Longbing Cao, and Zhendong Niu. Frequency-domain MLPs are more effective learners in time series forecasting. *Advances in Neural Information Processing Systems*, 36:76656–76679, 2023.

Ailing Zeng, Muxi Chen, Lei Zhang, and Qiang Xu. Are Transformers effective for time series forecasting? In *AAAI*, volume 37, pp. 11121–11128, 2023.

Yunhao Zhang and Junchi Yan. Crossformer: Transformer utilizing cross-dimension dependency for multivariate time series forecasting. In *ICLR*, 2023.

Siru Zhong, Weilin Ruan, Ming Jin, Huan Li, Qingsong Wen, and Yuxuan Liang. Time-VLM: Exploring multimodal vision-language models for augmented time series forecasting. In *Proceedings of the 42nd International Conference on Machine Learning (ICML)*, volume 267 of *PMLR*, pp. 78478–78497, 2025.

Haoyi Zhou, Shanghang Zhang, Jieqi Peng, Shuai Zhang, Jianxin Li, Hui Xiong, and Wancai Zhang. Informer: Beyond efficient transformer for long sequence time-series forecasting. In *AAAI*, 2021.

Shiqiao Zhou, Holger Schöner, Huanbo Lyu, Edouard Fouché, and Shuo Wang. BALM-TSF: Balanced multimodal alignment for LLM-based time series forecasting. arXiv:2509.00622, 2025. Preprint.

Tian Zhou, Ziqing Ma, Xue Wang, Qingsong Wen, Liang Sun, Tao Yao, Wotao Yin, and Rong Jin. FiLM: Frequency improved legendre memory model for long-term time series forecasting. *Advances in Neural Information Processing Systems*, 2022a.

Tian Zhou, Ziqing Ma, Qingsong Wen, Xue Wang, Liang Sun, and Rong Jin. FEDformer: Frequency enhanced decomposed transformer for long-term series forecasting. In *ICML*, 2022b.

Enqiang Zhu, Zhenbin Deng, Shengzhi Wang, Yi-Kun Tang, and Chanjuan Liu. PA-RNet: Perturbation-aware residual network for robust multimodal time series forecasting. *arXiv preprint arXiv:2508.04750*, 2025.

A Summary of Claims, Evidence, and Anticipated Questions

This section collects, in one place, the claims made in the main text and the experiments that support each of them, followed by answers to questions that the results naturally raise. It introduces no new results. Every number below is taken from a table or figure referenced alongside it.

A.1 Claims and Supporting Evidence

Table 6: **Map from each claim to its supporting evidence.** Ranks are Friedman average ranks over $N = 2016$ settings and $k = 11$ methods (lower is better, Appendix Q.1). Normalized MSE is from Figure 3d (lower is better).

	Claim	Evidence	Where
C1	Naive fusion often underperforms the unimodal model.	The unimodal baseline (rank 5.411) outranks *all six* naive variants (ranks 6.012–7.822). Only Additive-Middle/Last (0.333/0.334) beat the unimodal normalized MSE (0.349), and the other four naive variants are worse (0.364–0.621).	Fig. 1, Tab. 20
C2	Constrained fusion outperforms naive fusion.	All four constrained strategies (ranks 4.473–5.585) outrank every naive strategy (ranks 6.012–7.822), and all four attain lower normalized MSE (0.256–0.317) than every naive strategy (0.333–0.621).	Fig. 3d, Tab. 20
C3	CFA is the best of the compared methods.	Best average rank (4.473), significantly better than each of the other 10 methods under Nemenyi at $\alpha = 0.05$. Over 3 seeds, normalized MSE 0.256 ± 0.004, better than every baseline under a paired Wilcoxon test ($p < 0.01$).	Tab. 20, Tab. 19, Fig. 13
C4	The gains are general rather than setting-specific.	CFA improves over the unimodal model on $9/9$ datasets (first on $7/9$), on $13/14$ TS backbones, and is the best fusion strategy for each of the 4 text encoders.	Fig. 3a–3c
C5	CFA is a lightweight plug-in.	$+0.61\%$ parameters and $+0.04\%$ FLOPs over the unimodal model, with no change to the backbone. For comparison, Gating adds $+28.62\%$ and $+31.26\%$.	Tab. 5
C6	The low-rank bottleneck filters misaligned text.	In the controlled study, the bottleneck reduces MSE for matching ($+12.19\%$), contradicting ($+4.59\%$), and irrelevant ($+20.04\%$) text, and injects matching text more strongly than contradicting text ($p < 0.001$, $d = 0.58$). With cross-dataset irrelevant text, CFA stays closest to the unimodal model.	Fig. 4, Fig. 5, App. J
C7	The findings are not specific to Time-MMD.	On a text-paired ETT benchmark (96 settings), no naive variant reliably beats the unimodal model, while CFA is the only method that improves on it in both MSE and MAE ($+1.42\%$ MSE, $57/39$ win/loss) and has the lowest MSE among the compared methods on all 4 ETT datasets.	Tab. 21, App. R
C8	The gains do not come from leakage.	Text is paired only with the lookback window, and every text precedes the forecast horizon.	Sec. 3, App. G.1

A.2 Anticipated Questions

Q1. Is CFA simply LoRA applied to fusion? CFA borrows a LoRA-style *parameterization*, and we state this explicitly (Section 3.3). What differs is the object being constrained. LoRA constrains a *weight update* of a single model, and low-rank fusion methods constrain a *joint* representation in which the modalities are symmetric. CFA instead constrains the *injected cross-modal signal*, treating TS as the primary modality and text as an auxiliary one (Appendix D, Table 7). Our main contribution is the finding in C1–C2 that *how much* text enters determines whether it helps, and CFA is its simplest plug-in realization, applicable to all 14 backbones unchanged.

Q2. The margin of CFA over Gating is small. Is it meaningful? The margin is modest, and we do not overstate it. CFA's rank advantage over Gating (0.361) exceeds the Nemenyi critical difference at $\alpha = 0.05$ (0.336) but not at $\alpha = 0.01$ (0.386), and CFA wins 1049, ties 96, and loses 871 of the 2016 settings (Table 20). However, Gating needs $+28.62\%$ parameters, about $47\times$ CFA's overhead (Table 5), and falls below the unimodal model on text-paired ETT (-1.14% MSE), where CFA improves on it ($+1.42\%$, Table 21). Our central claim does not depend on this margin, since Gating is itself a constrained strategy.

Q3. Do the gains come from the text, or merely from added parameters? Three observations indicate that added capacity is not the explanation. (i) Several strategies add more parameters than CFA yet rank lower, such as Concat-Middle ($+12.33\%$ parameters, rank 6.169) and Gating ($+28.62\%$, rank 4.834), compared with CFA ($+0.61\%$, rank 4.473). (ii) In the controlled study, injecting text through the adapter beats injecting it directly (middle-additive) for every text type, most of all for irrelevant text (Figure 4). (iii) When the paired text is replaced by text from other datasets, CFA no longer improves on the unimodal model and instead stays close to it (Figure 5). A gain driven by extra parameters alone would persist under this substitution.

Q4. Could the results reflect uneven hyperparameter tuning? No method receives a larger tuning budget than another. Every method, including the unimodal baseline, is trained with the same sweep of 10 learning rates, the same epochs and early stopping, and the same data splits (Appendix H). The comparison therefore isolates the fusion strategy rather than the tuning effort.

Q5. Why are most experiments on Time-MMD? Time-MMD is, to our knowledge, the largest public benchmark with genuinely paired text and TS, covering nine domains. To test whether our conclusions depend on it, we additionally construct a text-paired version of ETT, where the same pattern reappears (C7, Appendix R). We list broader benchmark coverage as a limitation in Appendix B.

Q6. Why is there no text-only baseline? Forecasting extrapolates a numerical history, and the paired text is sparse commentary rather than a transcript of the series. A text-only model therefore reduces to a dataset-level prior, and the standard protocol in this literature compares TS+Text against a TS-only model (Appendix G.2).

Q7. Why does CFA not improve the vanilla Transformer? The vanilla Transformer is the weakest backbone in our study. CFA improves every TS-specific Transformer variant in our study (e.g., Nonstationary Transformer, iTransformer, Crossformer), so the exception likely lies in the backbone rather than in the fusion (Section 4.2).

Q8. How does CFA compare with architecture-specific multimodal models? Applied to an unmodified backbone, CFA attains the lowest average MSE on 4 of the 8 datasets (Agriculture, Public Health, Security, Social Good) and the second lowest on Energy. The concurrent architecture-specific model SpecTF is best on Climate, Energy, and Traffic, and TaTS on Economy (Table 25). Unlike these models, CFA requires no change to the TS architecture.

Q9. What does the theoretical analysis establish, and what does it not? Appendix L establishes a structural property: the textual signal injected by CFA lies in a subspace of dimension at most D/r, while the TS representation keeps all D dimensions. It does not provide a guarantee on forecasting error. The claim that this constraint filters misaligned text is supported empirically by the controlled study (C6), and a formal characterization is left for future work (Appendix B).

Q10. Is the method sensitive to the rank? Only mildly. The overall average MSE varies by less than 1% across $r \in \{2, 4, 8, 16, 32\}$, although individual datasets vary more, and we use $r = 8$ throughout (Appendix P, Table 14).

B LIMITATIONS

While our work establishes the importance of constrained fusion for multimodal time series forecasting, several limitations remain.

Modality coverage. Our study focuses on textual modalities paired with time series, leaving the extension of constrained fusion to other modalities such as vision and tabular data (Ekambaram et al., 2020; Chattopadhyay et al., 2024) as a promising direction for future work.

Language coverage. All datasets we evaluate (Time-MMD) provide *English* text descriptions, and all text encoders we adopt (BERT, GPT-2, Llama-3, Doc2Vec) are predominantly English-pretrained. Validating that the constrained fusion principle transfers to multilingual or low-resource language settings remains for future work.

Benchmark scope. Our evaluation is centered on the Time-MMD benchmark, which currently provides the most diverse public collection of paired text–time-series data across nine domains. Empirically confirming our findings on additional multimodal time-series benchmarks would further strengthen the generality of constrained fusion.

Theoretical understanding. Although CFA shows consistent improvements across diverse settings, our analysis is largely empirical. A more formal characterization of when low-rank adapters suppress misaligned auxiliary signals, and of how the bottleneck rank r interacts with the intrinsic dimension of the text representation, would deepen the theoretical foundation of constrained fusion.

C UNIMODAL TS FORECASTING MODELS

Recent TS forecasting methods employ Transformers (Vaswani et al., 2017) to capture temporal and channel dependencies. PatchTST (Nie et al., 2023) segments TS into patches and adopts channel-independent modeling. Crossformer (Zhang & Yan, 2023) captures channel interactions via hierarchical attention. iTransformer (Liu et al., 2024b) applies attention across features to model channel dependencies. Nonstationary Transformer (Liu et al., 2022) models non-stationarity within attention to address distribution shifts. Several works adopt lightweight architectures without attention, where DLinear (Zeng et al., 2023) uses linear decomposition to capture trend and seasonal components. TSMixer (Chen et al., 2023) employs MLP-based mixing across temporal and feature dimensions. TiDE (Das et al., 2023) employs an MLP-based encoder-decoder with temporal embeddings. FiLM (Zhou et al., 2022a) introduces a Frequency-improved Legendre Memory model with Legendre projection and Fourier denoising. Koopa (Liu et al., 2023) learns latent linear dynamics through Koopman operator.

D Relation to Low-Rank and Multimodal Fusion Methods

Our method is a low-rank module for multimodal fusion, and the terms *low-rank*, *multimodal*, and *fusion* also appear in several established lines of work. We therefore clarify how constrained fusion differs from them at the level of both the *problem* and the *mechanism*.

D.1 Low-Rank Multimodal Fusion

A first line of work uses low-rank structure to build a *joint* representation from several modalities. LMF (Liu et al., 2018) decomposes the multimodal fusion tensor into modality-specific low-rank factors, avoiding the cost of the full outer product. It has been combined with multimodal Transformers (Sahay et al., 2020), extended with backward connections between fusion stages (Shankar et al., 2022), and generalized to mixture-of-experts routing (Han et al., 2024).

These methods treat modalities **symmetrically**, where every modality contributes to a shared latent space, and their target tasks have no single dominant modality.

Our setting differs in exactly this respect. In multimodal TS forecasting, TS is the **primary** modality to be extrapolated, while text is an **auxiliary** signal that is only sometimes informative (Section 3). The phenomenon we study, where unconstrained fusion *degrades* an otherwise strong primary modality (Figure 1), does not arise under a symmetric formulation. Our remedy is correspondingly asymmetric, as the auxiliary signal is *filtered* before it perturbs the temporal representation.

D.2 Low-Rank Weight Adaptation

A second line of work applies low-rank structure to *model weights* for parameter-efficient adaptation. LoRA (Hu et al., 2022) constrains weight updates to a low-rank subspace. It has been specialized to TS forecasting (Nie et al., 2024) and extended to fusing a new modality into a pretrained LLM (Palaskar et al., 2024), among others.

CFA borrows the low-rank *parameterization* of this family, as stated in Section 3.3, but the constrained object differs. These methods constrain a **weight update** for efficiency, so the backbone is modified. CFA instead constrains the **injected cross-modal signal** for filtering, so the backbone is left untouched and the low rank is the mechanism that suppresses misaligned text (Appendix L). Efficiency is a by-product, as CFA adds only 0.61% parameters and 0.04% FLOPs (Table 5).

D.3 Capacity Asymmetry

CFA may appear to combine the two modalities symmetrically, since the fused representation is the sum $\mathbf{z}_{\mathrm{TS},t} + \mathbf{z}''_{\mathrm{Adapter},t}$. However, the asymmetry lies in the **capacity** of each path rather than in the form of the sum. As shown in Appendix L, the text term is confined to the column space of $\mathbf{W}_{\mathrm{up}}$, so it lies in a subspace of dimension at most D/r, whereas the TS term retains the full D dimensions. Text can thus move the representation only along restricted directions, and the temporal signal cannot be overwritten. This capacity asymmetry, rather than the algebraic form of the fusion operator, distinguishes constrained fusion from naive fusion (Table 7).

Table 7: **Positioning of CFA relative to low-rank and multimodal fusion methods.** *Constrained object* denotes what the low-rank structure is applied to.

Family	Representative works	Modality roles	Backbone	Constrained object
Low-rank multimodal fusion	Liu et al. (2018), Sahay et al. (2020)	Symmetric	Replaced	Joint interaction tensor
	Shankar et al. (2022), Han et al. (2024)	Symmetric	Replaced	Fusion architecture
Low-rank weight adaptation	Hu et al. (2022), Nie et al. (2024)	Single modality	Modified	Weight update
	Palaskar et al. (2024)	Asymmetric	Modified	Weight update
Constrained fusion (CFA)	**Ours**	**Asymmetric**	**Preserved**	**Injected cross-modal signal**

E DETAILS OF MODELS

We use the `mmtslib` package provided by Time-MMD (Liu et al., 2024a). We adopt 14 TS models and 4 text models implemented in the library.

Why these backbones. Our aim is to show that constrained fusion generalizes *across* architectures rather than to identify the strongest forecaster, so we adopt the established architectures already implemented in the Time-MMD library (Liu et al., 2024a). The resulting set spans 9 Transformer-based, 3 Linear/MLP-based, and 2 other backbones (Table 3). Newer unimodal forecasters are *orthogonal* to our contribution, since they are backbones rather than fusion strategies. The relevant comparison axis is the *fusion* axis, along which we evaluate 10 strategies (Table 3) and compare against architecture-specific models in Appendix S.

TS Models. We use 14 TS models from three categories as follows:

- **Transformer-based Models**
  - **Transformer** (Vaswani et al., 2017): A standard sequence-to-sequence model based on multi-head self-attention.
  - **Informer** (Zhou et al., 2021): A sparse-attention Transformer designed for efficient long-term TS forecasting.
  - **Reformer** (Kitaev et al., 2020): An efficient Transformer variant using locality-sensitive hashing and reversible layers.
  - **Autoformer** (Wu et al., 2021): A decomposition-based Transformer that replaces attention with an auto-correlation mechanism.
  - **FEDformer** (Zhou et al., 2022b): A frequency-enhanced Transformer leveraging Fourier decomposition for long-horizon prediction.
  - **Crossformer** (Zhang & Yan, 2023): A multivariate Transformer that models cross-dimension dependencies.
  - **iTransformer** (Liu et al., 2024b): An inverted Transformer that treats variates as tokens to model inter-variable relationships.
  - **Nonstationary Transformer** (Liu et al., 2022): A Transformer tailored to capture non-stationary temporal patterns.
  - **PatchTST** (Nie et al., 2023): A patch-based Transformer that segments TS into subseries tokens for scalable forecasting.
- **Linear / MLP-based Models**
  - **DLinear** (Zeng et al., 2023): A linear model that performs forecasting via direct regression on historical inputs.
  - **TiDE** (Das et al., 2023): An MLP-based encoder-decoder model designed for long-term TS forecasting.
  - **TSMixer** (Chen et al., 2023): A fully-MLP architecture that mixes temporal and feature information for prediction.
- **Other Architectures**
  - **Koopa** (Liu et al., 2023): A Koopman-operator-inspired model that decomposes TS into stable and dynamic components.
  - **FiLM** (Zhou et al., 2022a): A frequency-based method that applies Fourier and Legendre projections for denoising and trend modeling.

Text Models. We use 4 text models, including three LLMs as follows:

- **BERT** (Devlin et al., 2019): A bidirectional Transformer pre-trained with masked language modeling.
- **GPT-2** (Radford et al., 2019): An autoregressive Transformer trained to predict next-token distributions.
- **Llama-3** (Grattafiori et al., 2024): A recent large language model with improved text generation and comprehension capabilities.
- **Doc2Vec** (Le & Mikolov, 2014): A model learning fixed-length document vectors.

F DETAILS OF DATASETS

We use the nine multimodal datasets from various domains proposed in Time-MMD (Liu et al., 2024a). The input length (L) and forecasting horizons (H) are determined according to the frequency of each dataset. Detailed information about the datasets is provided in Table 8. The qualitative descriptions of each dataset are as follows:

- **Agriculture**: Tracks U.S. retail broiler composite prices, reflecting supply–demand dynamics and seasonal patterns in the agricultural market.
- **Climate**: Measures drought severity levels across regions, capturing long-term climate variability and extreme weather trends.
- **Economy**: Represents the U.S. international trade balance, indicating macroeconomic conditions and global trade fluctuations.
- **Energy**: Records U.S. gasoline prices, a key indicator of energy market volatility.
- **Environment**: Monitors daily air quality index (AQI), reflecting pollution dynamics and environmental risk levels.
- **Public Health**: Tracks weekly influenza-like illness (ILI) proportions, serving as a proxy for epidemic spread and public health trends.
- **Security**: Captures disaster and emergency grant allocations, reflecting the temporal impact of large-scale natural and societal crises.
- **Social Good**: Measures unemployment rates, highlighting labor market disparities and socioeconomic stability.
- **Traffic**: Represents travel volume, indicating mobility trends and transportation dynamics.

Table 8: **Meta information of the nine Time-MMD (Liu et al., 2024a) datasets.** We report the domain, prediction target, dimensionality, data frequency, number of samples, timespan, input length (L), and forecasting horizons (H) for all nine multimodal datasets.

Domain	Target	Dim.	Freq.	#Samples	Timespan	L	H
Agriculture	Retail Broiler Composite	1	M	496	1983–Present	8	{6, 8, 10, 12}
Climate	Drought Level	5	M	496	1983–Present	8	{6, 8, 10, 12}
Economy	International Trade Balance	3	M	423	1989–Present	8	{6, 8, 10, 12}
Energy	Gasoline Prices	9	W	1479	1996–Present	36	{12, 24, 36, 48}
Environment	Air Quality Index	4	D	11102	1982–2023	96	{48, 96, 192, 336}
Public Health	Influenza Patients Proportion	11	W	1389	1997–Present	36	{12, 24, 36, 48}
Security	Disaster & Emergency Grants	1	M	297	1999–Present	8	{6, 8, 10, 12}
Social Good	Unemployment Rate	1	M	900	1950–Present	8	{6, 8, 10, 12}
Traffic	Travel Volume	1	M	531	1980–Present	8	{6, 8, 10, 12}

G TEXT–TIME SERIES PAIRING AND TEXT QUALITY

G.1 TEMPORAL ALIGNMENT AND THE ABSENCE OF LOOK-AHEAD BIAS

A natural concern in multimodal TS forecasting is whether the auxiliary text leaks information about the forecast horizon. Such leakage would make any reported gain an artifact rather than a modeling result. Our formulation excludes this by construction.

As stated in Section 3, the model receives a lookback window $\mathbf{x} = (\mathbf{x}_1, \ldots, \mathbf{x}_L)$ and a paired text sequence $\mathbf{t} = (\mathbf{t}_1, \ldots, \mathbf{t}_L)$ of the *same* length L. It then predicts $\mathbf{y} = (\mathbf{x}_{L+1}, \ldots, \mathbf{x}_{L+H})$. Text is indexed only up to L and is never paired with any step in the horizon H. Time-MMD (Liu et al., 2024a) timestamps each text report and assigns it to the step at which it was published. A report that appeared after time L is therefore not visible to the model. No text used at prediction time postdates the lookback window, so no information about $(\mathbf{x}_{L+1}, \ldots, \mathbf{x}_{L+H})$ can enter through the text channel.

The same property holds for the text-paired ETT benchmark we construct in Appendix R, where each description is generated *strictly* from values preceding its own timestamp.

G.2 ON THE TEXT-ONLY BASELINE

Given a TS-only baseline and a TS+Text model, one may ask for a Text-only baseline to complete the ablation. We report results without one. We explain below why such a baseline is not well posed for this task, rather than an omission.

TS forecasting is the problem of extrapolating a numerical trajectory from its own past values. A model with no TS input has no trajectory to extrapolate from. The text in these benchmarks is sparse contextual commentary such as news snippets and situation reports, not a numerical transcript of the series. The ordering of $\mathbf{t}_1, \ldots, \mathbf{t}_L$ does not repair this, since an ordered sequence of text is still not a quantitative history. Such a model can at best reproduce a dataset-level prior. It is therefore a degenerate lower bound rather than a competitive baseline, and comparing against it would inflate the reported gains rather than test them.

Accordingly, the established convention in the multimodal TS forecasting literature (Liu et al., 2024a; Jin et al., 2024; Jia et al., 2024; Li et al., 2025; Kim et al., 2024) is to benchmark TS+Text against a TS-only baseline, which is the protocol we follow throughout (Tables 3 and 4). The relevant question is not whether text alone can forecast. It is whether adding text to a strong unimodal forecaster helps or hurts, which is what this paper measures.

G.3 TEXT QUALITY: MISALIGNMENT VERSUS NOISE

Failures of naive fusion are often attributed to "noisy text." However, this phrase conflates two distinct failure modes, which call for different diagnoses.

- **Misalignment.** The text is *about* the series but disagrees with it. One example is a report anticipating a downturn while the series is rising. The signal is topically relevant and therefore passes through any relevance-based filter, yet it pushes the representation in the wrong direction. This is the **contradicting** case in our controlled study (Appendix J).
- **Noise.** The text is unrelated to the series altogether and carries no forecasting signal in either direction. It should ideally be ignored rather than corrected for. This is the **irrelevant** case (Appendix J) and the setting of the cross-dataset experiment in Section 5.

The distinction matters because the two degrade a forecaster differently. Table 9 summarizes what our controlled experiments show. Matching text is the only category that helps. The low-rank bottleneck improves every category, with the largest margin on irrelevant text ($+20.04\%$), where there is nothing to preserve. The smallest margin is on contradicting text ($+4.59\%$), where the misaligned signal is topically indistinguishable from a useful one. Without the bottleneck, the ordering is inverted. Contradicting text yields *lower* error than matching text, indicating that an unconstrained model treats

all text as undifferentiated perturbation rather than as content (Appendix J.1). The representation analysis confirms that the constrained model discriminates between the two, since matching text is injected more strongly than contradicting text ($t = 4.03$, $p < 0.001$, $d = 0.58$, Appendix J.2).

Table 9: **When does text help, and what does the bottleneck do?** Categories follow the controlled study of Appendix J. Improv. is the relative MSE reduction of CFA (w/ bottleneck) over the middle-additive baseline (w/o bottleneck), from Table 13.

Text type	Failure mode	Effect on forecasting	Improv. (%)	Role of the low-rank bottleneck
Matching	None	Helpful	+12.19	Preserves the aligned component
Contradicting	Misalignment	Most harmful	+4.59	Attenuates a topically plausible but wrong signal
Irrelevant	Noise	Neutral to harmful	+20.04	Suppresses the signal almost entirely

This also answers a question that the aggregate results leave open, namely whether the paired text in Time-MMD is informative at all. Our results measure this rather than assume it. If the text were pure noise, no fusion strategy should consistently beat the unimodal baseline, yet CFA does so on all 9 datasets (Figure 3a). If it were uniformly informative, naive fusion would not fall below the unimodal baseline, yet it frequently does (Figure 1). Real paired text is therefore *partially* informative and *partially* misaligned, which is exactly the regime in which constrained fusion is needed.

G.4 Construction of the Irrelevant-Text Experiment

The irrelevant-text experiment of Section 5 is constructed as follows. For each of the nine Time-MMD datasets, we keep the TS input unchanged and replace each aligned text with a text drawn uniformly at random from the *other eight* datasets. For example, a sample from Agriculture keeps its broiler-price series but receives a report drawn from, say, Economy or Climate. Sampling is performed once per evaluation with a fixed seed, so that all fusion strategies see identical substituted text. Every other component of the protocol is held fixed at the values used in the main experiments, including the backbone, the text encoder, the horizon, and the learning-rate sweep. The result is $500+$ settings spanning all TS backbones, datasets, and horizons.

Three properties of this design are worth stating explicitly.

It is a stress test, not the basis of our main claim. All headline results (Table 4, Figure 3a) use the *real* aligned text. The substituted-text experiment is a robustness diagnostic that asks what a fusion strategy does when its auxiliary input becomes uninformative, and it is reported as such.

The substituted text is realistic, not synthetic. The replacement text consists of genuine reports written by humans about real-world domains. Only its *pairing* with the series is broken. The setting therefore models a concrete and common deployment failure, where a text feed becomes stale, is mis-joined, or drifts to a different topic. It is not an adversarially constructed input.

It is not favorable to CFA by construction. The manipulation is applied identically to every fusion strategy and no method is tuned on it. A method that simply ignores text would score perfectly here. CFA does not ignore text, and yet it is the strategy that stays closest to the unimodal baseline (Figure 5). The complementary controlled study on synthetic data (Appendix J), where text quality is manipulated by construction rather than by resampling, reaches the same conclusion, so the finding does not rest on this design alone.

H EXPERIMENTAL SETUP

(1) Evaluation metrics. We evaluate forecasting performance using Mean Squared Error (MSE) and Mean Absolute Error (MAE), which are standard metrics in TS forecasting.

(2) Input and output horizons. We employ different forecasting horizon settings depending on the frequency of each dataset, as shown in Table 10.

(3) Optimizer. We use the Adam optimizer (Kingma & Ba, 2014) for all modules, with batch size 32.

(4) Learning rate. We assign separate optimizers and learning rates to different components, with the default values listed in Table 11. Default learning rates are scaled by $\{0.05, 0.1, 0.5, 1.0, 2.0, 5.0, 10.0, 20.0, 50.0, 100.0\}$ to obtain 10 learning rate configurations per component, from which the best configuration is selected.

Table 10: Input and output horizon settings.

Frequency	L	H
Daily	96	[48, 96, 192, 336]
Weekly	36	[12, 24, 36, 48]
Monthly	8	[6, 8, 10, 12]

Table 11: Learning rate configuration.

Target module	Learning rate	Default value
TS Model	η_{TS}	1×10^{-4}
Text Embedding MLP	η_{MLP}	1×10^{-2}
Projection Layer	η_{Proj}	1×10^{-3}

(5) Epochs. We train the model for a maximum of 10 epochs with patience 5.

(6) Data split. All datasets are divided chronologically into train:validation:test = 7:1:2.

(7) Aggregated metric. When results are aggregated across datasets whose error scales differ by orders of magnitude, we report normalized MSE following Time-MMD (Liu et al., 2024a).

(8) Compute resource. All experiments are conducted on a single NVIDIA L40-48G GPU.

I MODEL HYPERPARAMETERS

Table 12 presents the hyperparameter settings of the 14 TS models used in our experiments. We follow the default configurations adopted in Time-MMD (Liu et al., 2024a). Here, d_{model} denotes the model (hidden) dimension, n_{heads} the number of attention heads, $L_{\text{enc}}/L_{\text{dec}}$ the number of encoder/decoder layers, d_{ff} the feed-forward dimension, and p_{drop} the dropout rate.

Note that since DLinear (Zeng et al., 2023) has no hidden representation, all three injection positions (first, middle, and last) operate directly on the channel dimension C_{in} rather than a latent dimension d_{model}. Specifically, first fusion adds or concatenates the projected text embedding $\mathbf{W}_{\text{proj}}\mathbf{e}_t \in \mathbb{R}^{C_{\text{in}}}$ to the raw input $\mathbf{x} \in \mathbb{R}^{L\times C_{\text{in}}}$ before decomposition. Middle fusion injects the text signal into the seasonal and trend components $\in \mathbb{R}^{C_{\text{in}}\times H}$ independently after the `seq_len` $\rightarrow$ `pred_len` linear projection but before their summation. Last fusion modifies the final output $\in \mathbb{R}^{H\times C_{\text{in}}}$ after the linear mapping. For CFA, the bottleneck dimension is computed as $\lfloor C_{\text{in}}/r \rfloor$ rather than $\lfloor d_{\text{model}}/r \rfloor$. Thus, the low-rank text residual is injected into the variate space instead of a token- or hidden-level space.

Table 12: Default hyperparameters of the 14 TS models.

Model	d_{model}	n_{heads}	L_{enc}	L_{dec}	d_{ff}	p_{drop}
Transformer-based methods						
Transformer (Vaswani et al., 2017)	512	8	2	1	2048	0.1
Informer (Zhou et al., 2021)	512	8	2	1	2048	0.1
Autoformer (Wu et al., 2021)	512	8	2	1	2048	0.1
FEDformer (Zhou et al., 2022b)	512	8	2	1	2048	0.1
Nonstationary Transformer (Liu et al., 2022)	512	8	2	1	2048	0.1
Reformer (Kitaev et al., 2020)	512	8	2	—	2048	0.1
iTransformer (Liu et al., 2024b)	512	8	2	—	2048	0.1
PatchTST (Nie et al., 2023)	512	8	2	—	2048	0.1
Crossformer (Zhang & Yan, 2023)	512	8	2	—	2048	0.1
Linear/MLP-based methods						
DLinear (Zeng et al., 2023)	—	—	—	—	—	0.1
TSMixer (Chen et al., 2023)	512	—	2	—	—	0.1
TiDE (Das et al., 2023)	512	—	2	1	2048	0.1
Others						
FiLM (Zhou et al., 2022a)	512	—	2	—	—	0.1
Koopa (Liu et al., 2023)	—	—	—	—	—	0.1

J TOY EXPERIMENT

We conduct a controlled toy experiment to analyze *the effect of the low-rank bottleneck (low-rank adapter)* in CFA. The low-rank adapter constrains the projection of text embeddings through a low-rank bottleneck before they are injected into the TS backbone, which is expected to *suppress irrelevant or contradicting textual signals while preserving useful guidance*.

To examine this effect, we compare CFA with and without the low-rank constraint. Throughout this section, **w/ bottleneck** denotes CFA with the low-rank bottleneck, while **w/o bottleneck** denotes the middle-additive baseline that directly injects text embeddings without the low-rank constraint.

A. Toy dataset construction. We synthesize a univariate TS and pair each time step with a short natural-language description. Each description belongs to one of three categories:

- 1) **Matching:** The description correctly reflects the current trend of the TS (*e.g.*, "The value is rising steadily"). This text provides useful information and should be incorporated by the model.
- 2) **Contradicting:** The description contradicts the actual trend (*e.g.*, "The value is declining" when TS is rising). Injecting such text without filtering is expected to degrade performance.
- 3) **Irrelevant:** The description is unrelated to the TS (*e.g.*, a sentence about an unrelated domain). This text contains no useful signal and should ideally be ignored.

We construct a dataset ($N = 1{,}000$) in which all three text types coexist, with a 70/10/20 train, validation, and test split. Figure 8 shows example TS segments paired with each text type.

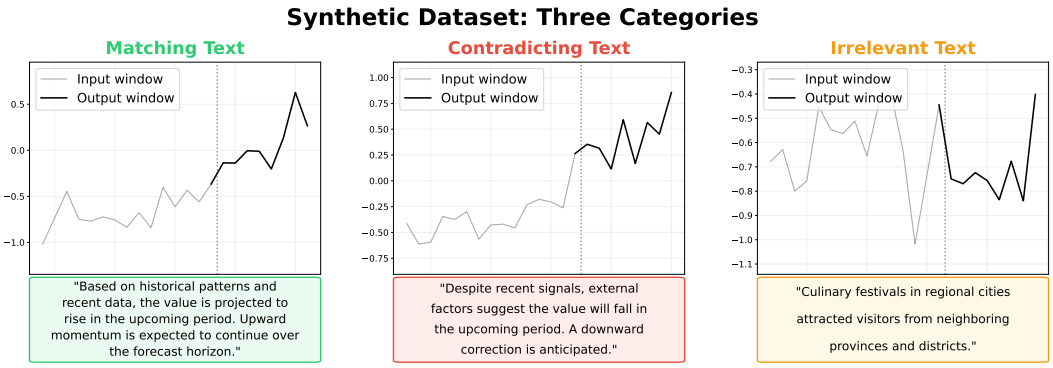


Figure 8: **Illustration of the toy dataset**. Each time step of the TS is paired with a text description, categorized as 1) matching, 2) contradicting, or 3) irrelevant. Matching descriptions align with the TS trend, contradicting ones oppose it, and irrelevant ones provide no useful signal.

B. Model and horizon. We use the Nonstationary Transformer (Liu et al., 2022) as the TS backbone with an input length of $L = 8$ and a prediction horizon of $H = 8$.

C. Analyses. We examine the effect of the low-rank bottleneck from three perspectives:

- **Performance comparison** (Sec J.1): MSE per text type.
- **Representation analysis** (Sec J.2): Bottleneck activation norms and text-contribution ratios.
- **TS visualization** (Sec J.3): Predictions for matched vs. contradicting text.

J.1 Analysis 1: Performance Comparison

Table 13 reports the MSE on the test split for case w/ bottleneck (CFA) and w/o bottleneck (middle-additive) across three categories of text descriptions. Three observations follow.

Filtering, not capacity. Before the individual observations, this table settles a question the main results cannot: whether CFA improves forecasting because it *filters* misaligned text or simply because it *adds parameters*. The two variants differ in how text enters the backbone: directly (middle-additive), or through the low-rank adapter, which also applies LayerNorm and ReLU. The adapter variant wins on every text type, and by the largest margin where the text is least useful (irrelevant, $+20.04\%$). Parameter count alone does not explain this pattern. In the main experiments, strategies that add far more parameters than CFA, such as Concat-Middle ($+12.33\%$) and Gating ($+28.62\%$), rank below it (Table 20), while CFA adds only 0.61% parameters and 0.04% FLOPs over the unimodal backbone (Table 5). The mechanism is therefore selective suppression, which the representation analysis in Appendix J.2 confirms directly: matching text is injected significantly more strongly than contradicting text.

Table 13: **Performance on the synthetic dataset.** Results are reported for CFA w/ and w/o bottleneck across three categories of text descriptions.

Text type	w/o bottleneck	w/ bottleneck	Improv. (%)
Matching	0.1683	**0.1477**	+ 12.19
Contradicting	0.1635	**0.1560**	+ 4.59
Irrelevant	0.1851	**0.1480**	+ 20.04

(i) CFA improves performance across all text types. CFA (w/ bottleneck) achieves lower MSE than the middle-additive baseline (w/o bottleneck) for **matching**, **contradicting**, and **irrelevant** descriptions, *indicating that the low-rank bottleneck consistently improves multimodal fusion*.

(ii) CFA effectively suppresses irrelevant textual signals. For **irrelevant** descriptions, which contain no useful forecasting information, the middle-additive baseline still injects the text into the TS backbone, introducing noise into the representations. In contrast, the *low-rank bottleneck largely filters out such inputs*, yielding the largest MSE reduction ($+20.04\%$).

(iii) CFA better distinguishes helpful and harmful text. Without the low-rank adapter, **contradicting** text surprisingly yields lower MSE than **matching** text, suggesting that *the baseline fails to properly utilize the semantic content of the descriptions*. In contrast, with the low-rank adapter, the expected ordering emerges, where **matching** descriptions are most beneficial, while **contradicting** descriptions remain the most challenging ($\text{MSE}_{\text{Matching}} < \text{MSE}_{\text{Irrelevant}} < \text{MSE}_{\text{Contradicting}}$).

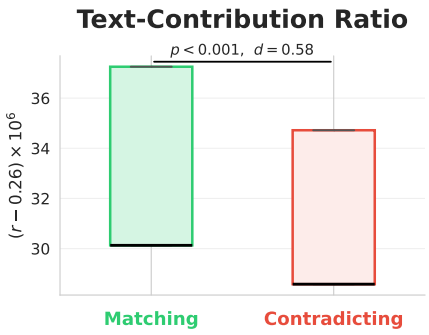
J.2 Analysis 2: Representation Analysis

To investigate how CFA selectively filters text, we measure the **text-contribution ratio** at the output of the low-rank adapter. For each test sample, we compute $r = \frac{\|\mathbf{o}\|_2}{\|\bar{\mathbf{e}}\|_2}$, where $\mathbf{o} \in \mathbb{R}^{d_{\text{model}}}$ is the adapter output added to the TS representation, and $\bar{\mathbf{e}}$ is the pooled text embedding before the adapter. Intuitively, r quantifies *how much of the original text signal survives the bottleneck*: higher r indicates stronger injection, while lower r indicates suppression. In this analysis, we focus on the first encoder layer of the Nonstationary Transformer and report r by text category (*Matching* vs. *Contradicting*).

Figure 9 summarizes the distribution of r for **matching** and **contradicting** text, where values are $(r - 0.25745) \times 10^6$ for readability. Matching text yields a higher mean value (33.50) than contradicting text (31.56), and the difference is statistically significant ($t = 4.03$, $p < 0.001$, Cohen's $d = 0.58$). This suggests that the low-rank bottleneck *suppresses contradictory text while preserving matching information*, providing controlled guidance to the TS backbone.

	Matching	**Contradicting**
Mean	33.50	31.56
Std	3.56	3.07
t, p	$t = 4.03, p < 0.001$	
Cohen's d	0.58	

(a) Statistics of text-contribution ratio.



(b) Distribution of text-contribution ratio.

Figure 9: **Text-contribution ratio.** (a) Matching text is injected more strongly than contradicting text, indicating that the adapter selectively suppresses conflicting information. (b) Distribution of text-contribution ratio for matching vs. contradicting text.

J.3 Analysis 3: TS Visualization

Figure 10 provides a qualitative comparison of the forecast trajectories for a representative matching (left) and contradicting (right) test sample.

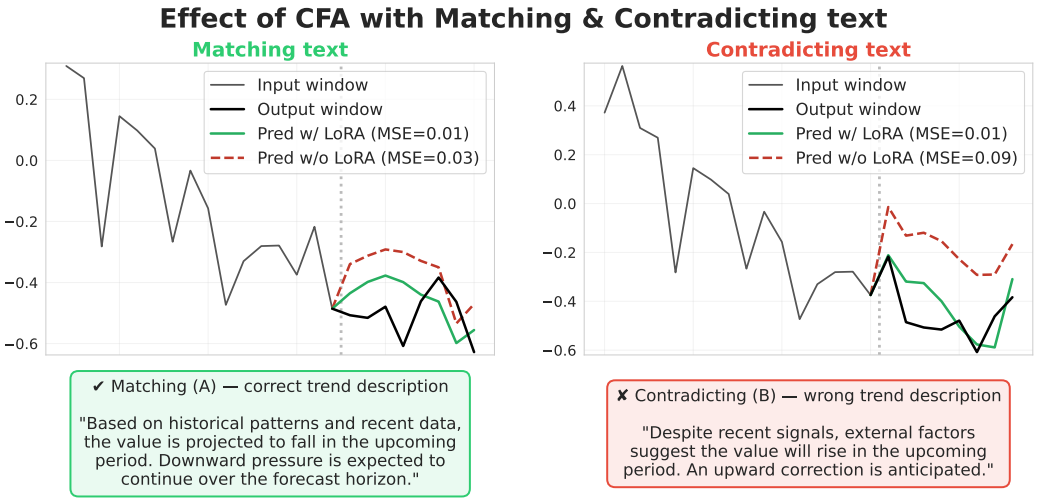


Figure 10: Forecast comparison for a matched (left) and a contradicting (right) text sample. **Green solid**: w/ bottleneck. **Red dashed**: w/o bottleneck. **Black solid**: ground truth. The vertical dotted line separates the input window from the prediction horizon.

Matching text. When the injected text correctly describes the trend, both w/ bottleneck and w/o bottleneck produce reasonable forecasts that follow the ground truth. The CFA prediction (w/ bottleneck) tracks the ground truth more closely, suggesting that *the low-rank bottleneck preserves useful information while using the helpful signal*.

Contradicting text. The contrast is clearer for the contradicting-text sample, where the ground truth descends during the forecast horizon, while the injected text suggests an upward movement. The baseline (w/o bottleneck) is misled by this conflicting signal and its prediction rises in the early forecast steps, deviating from the ground truth. CFA (w/ bottleneck), in contrast, disregards the misleading text and predicts a downward trajectory that closely follows the ground truth. This qualitative contrast visualizes the filtering capability of the bottleneck, as the low-rank constraint *prevents harmful text from corrupting the forecast even when the text is strongly contradictory*.

K Details of Constrained Fusion

In this section, we provide formal descriptions and mathematical formulations for the three constrained fusion strategies introduced in Section 3.2. We adopt the notation defined in Section 3: TS embeddings $\mathbf{Z}_{\text{TS}} = [\mathbf{z}_{\text{TS},1}, \ldots, \mathbf{z}_{\text{TS},L}]$, text embeddings $\mathbf{Z}_{\text{Text}} = [\mathbf{z}_{\text{Text},1}, \ldots, \mathbf{z}_{\text{Text},L}]$.

K.1 Gating Mechanism

The gating mechanism determines the relevance of textual information at each time step using a learned gate. Formally, let $\mathbf{z}_{\text{TS},t} \in \mathbb{R}^D$ denote the TS embedding at time step t, and $\mathbf{z}_{\text{Text},t} \in \mathbb{R}^D$ the text embedding. Then, a gate $\mathbf{g}_t \in [0,1]^D$ is computed as:

$$\mathbf{g}_t = \sigma(\mathbf{W}_g[\mathbf{z}_{\text{TS},t}; \mathbf{z}_{\text{Text},t}] + \mathbf{b}_g), \tag{2}$$

where σ is the sigmoid function, $[\cdot;\cdot]$ denotes concatenation, and $\mathbf{W}_g, \mathbf{b}_g$ are learnable parameters. The fused embedding is then:

$$\mathbf{z}_{\text{fused},t} = \mathbf{z}_{\text{TS},t} + \mathbf{g}_t \odot \mathbf{z}_{\text{Text},t}. \tag{3}$$

K.2 FiLM (Feature-wise Linear Modulation)

FiLM modulates TS embeddings using text embeddings via feature-wise scaling and shifting as:

$$\mathbf{z}_{\text{fused},t} = \boldsymbol{\gamma}(\mathbf{z}_{\text{Text},t}) \odot \mathbf{z}_{\text{TS},t} + \boldsymbol{\beta}(\mathbf{z}_{\text{Text},t}), \tag{4}$$

where $\boldsymbol{\gamma}(\cdot), \boldsymbol{\beta}(\cdot)$ are learned functions (e.g., MLPs) that generate scaling and shifting parameters from the text embedding. This preserves the temporal structure of TS embeddings while modulating each feature dimension according to textual context.

K.3 Orthogonal Fusion

Orthogonal fusion projects the text embedding onto the orthogonal complement of the TS embedding to avoid overwriting temporal information:

$$\mathbf{z}^{\perp}_{\text{Text},t} = \mathbf{z}_{\text{Text},t} - \frac{\mathbf{z}^{\top}_{\text{TS},t}\mathbf{z}_{\text{Text},t}}{\|\mathbf{z}_{\text{TS},t}\|^2}\mathbf{z}_{\text{TS},t}, \tag{5}$$

$$\mathbf{z}_{\text{fused},t} = \mathbf{z}_{\text{TS},t} + \mathbf{z}^{\perp}_{\text{Text},t}. \tag{6}$$

This ensures that only components of the text embedding orthogonal to the TS embedding are integrated, preserving the temporal information.

K.4 Controlled Fusion Adapter (CFA)

Controlled Fusion Adapter (CFA) integrates textual information into TS embeddings through a residual adapter with a low-dimensional bottleneck. Unlike direct additive or multiplicative fusion, CFA first transforms the text embedding into a compact latent space and then projects it back to the original dimension before residual addition. This design preserves the TS backbone representation while allowing text to provide directional guidance with minimal parameter overhead.

Formally, for each time step t, the text embedding $\mathbf{z}_{\text{Text},t} \in \mathbb{R}^D$ is first projected to a reduced bottleneck space:

$$\mathbf{z}_{\text{Adapter},t} = \mathbf{W}_{\text{down}}\mathbf{z}_{\text{Text},t} \in \mathbb{R}^{D/r}, \tag{7}$$

where r is the reduction ratio controlling parameter efficiency. The intermediate representation is then normalized and activated:

$$\mathbf{z}'_{\text{Adapter},t} = \phi\big(\text{LayerNorm}(\mathbf{z}_{\text{Adapter},t})\big), \tag{8}$$

where $\phi(\cdot)$ denotes a non-linear activation function (e.g., ReLU). Finally, the representation is projected back to the original dimension and added as a residual to the TS embedding:

$$\mathbf{z}_{\text{fused},t} = \mathbf{z}_{\text{TS},t} + \mathbf{W}_{\text{up}}\mathbf{z}'_{\text{Adapter},t}. \tag{9}$$

Here, $\mathbf{W}_{\text{down}} \in \mathbb{R}^{\frac{D}{r}\times D}$ and $\mathbf{W}_{\text{up}} \in \mathbb{R}^{D\times\frac{D}{r}}$ are learnable parameters. The residual structure ensures that the original TS embedding is preserved, while the bottleneck controls the magnitude and complexity of textual influence. In practice, initializing $\mathbf{W}_{\text{up}}$ near zero helps stabilize early training by preventing excessive perturbation of the TS backbone.

L Theoretical Perspective on Fusion

CFA injects textual signals into TS embeddings through a low-rank adapter. Following the formulation in Sec 3.3, the injected signal is given by

$$\mathbf{z}''_{\text{Adapter},t} = \mathbf{W}_{\text{up}}\,\phi\big(\text{LayerNorm}(\mathbf{W}_{\text{down}}\mathbf{z}_{\text{Text},t})\big), \tag{10}$$

which is added to the TS embedding as

$$\tilde{\mathbf{z}}_{\text{TS},t} = \mathbf{z}_{\text{TS},t} + \mathbf{z}''_{\text{Adapter},t}. \tag{11}$$

Since $\mathbf{W}_{\text{up}} \in \mathbb{R}^{D\times D/r}$, its column space has dimension at most D/r. For any intermediate vector $\mathbf{v} \in \mathbb{R}^{D/r}$ obtained by applying down-projection, LayerNorm, and non-linear activation ϕ, the output $\mathbf{W}_{\text{up}}\mathbf{v}$ lies in the column space of $\mathbf{W}_{\text{up}}$. Therefore the injected textual signal lies in a subspace of $\mathbb{R}^D$ whose dimension is at most D/r.

This low-rank constraint *restricts the directions in which textual signals influence TS embeddings*. As a result, the textual information modifies TS representations only *within a low-dimensional subspace*. This reduces the capacity of textual signals and suppresses irrelevant information.

M TEMPORAL ATTRIBUTION

To analyze which past time steps the model relies on when generating forecasts, we assign an importance score to each of the L input time steps. This enables direct comparison of temporal focus across different fusion strategies.

Problem setup. Let the encoder input be $\mathbf{x} \in \mathbb{R}^{B\times L\times D}$, where B denotes the batch size, L the input horizon, and D the number of channels. The forecasting model predicts $\hat{\mathbf{y}}$ over the output horizon, and we use MSE as the loss. Our goal is to quantify the contribution of each input time step $t \in \{0, \dots, L-1\}$ to this loss.

Gradient-based temporal importance. We adopt a Gradient $\times$ Input attribution scheme. For a single sample (omitting the batch index), let $x_t^{(d)}$ denote the input value at time step t and channel d. The gradient of the loss with respect to the input is

$$g_t^{(d)} = \frac{\partial \mathcal{L}}{\partial x_t^{(d)}}.$$

The element-wise attribution is defined as

$$a_t^{(d)} = g_t^{(d)} \cdot x_t^{(d)}.$$

We aggregate over channels to obtain one importance value per time step:

$$I_t = \sum_{d=1}^{D} \left| a_t^{(d)} \right| = \sum_{d=1}^{D} \left| \frac{\partial \mathcal{L}}{\partial x_t^{(d)}} \cdot x_t^{(d)} \right|.$$

This yields an importance vector $\mathbf{I} = (I_0, \dots, I_{L-1}) \in \mathbb{R}^L$. When the input horizon is $L = 8$, we therefore obtain exactly 8 importance values, one for each input time step.

For visualization and comparison across samples, we optionally normalize the scores:

$$\tilde{I}_t = \frac{I_t}{\sum_{t'=0}^{L-1} I_{t'} + \epsilon},$$

where $\epsilon > 0$ ensures numerical stability.

Implementation details We compute gradients with respect to the encoder input by cloning the input tensor and enabling gradient tracking on the clone. After a forward pass and backpropagation of the MSE loss, we extract $\partial\mathcal{L}/\partial\mathbf{x}$ and compute the element-wise product with the original input values. All attribution scores are computed under the same forecasting setting used for evaluation.

For models that do not employ attention mechanisms, such as TiDE, the temporal attribution is derived solely from the gradient-based formulation above. Thus, the number of importance values always equals the input horizon L, ensuring consistent interpretation across backbones.

N Representation Similarity Analysis

To quantify how text fusion reshapes temporal representations, we measure the cosine similarity between the layer-wise representations $\mathbf{Z}_\ell^{\text{TS}}$ and $\mathbf{Z}_\ell^{\text{TS+Text}}$ at layer ℓ, where $\ell \in \{1, \ldots, L\}$ denotes the layer index. We compute the layer-wise cosine similarity between $\mathbf{Z}_\ell^{\text{TS}}$ and $\mathbf{Z}_\ell^{\text{TS+Text}}$, and obtain the final similarity score by averaging across layers:

$$S = \frac{1}{L} \sum_{\ell=1}^{L} \frac{\left\langle \mathbf{Z}_\ell^{\text{TS}}, \mathbf{Z}_\ell^{\text{TS+Text}} \right\rangle}{\left\| \mathbf{Z}_\ell^{\text{TS}} \right\|_2 \left\| \mathbf{Z}_\ell^{\text{TS+Text}} \right\|_2}. \tag{12}$$

We repeat this analysis across different settings and fusion strategies. As shown in Figure 11, the best-performing fusion method (red) does not consistently correspond to the largest deviation from the unimodal baseline. This indicates that effective fusion requires *controlled modification* of temporal representations with textual information rather than simply increasing representation shift.

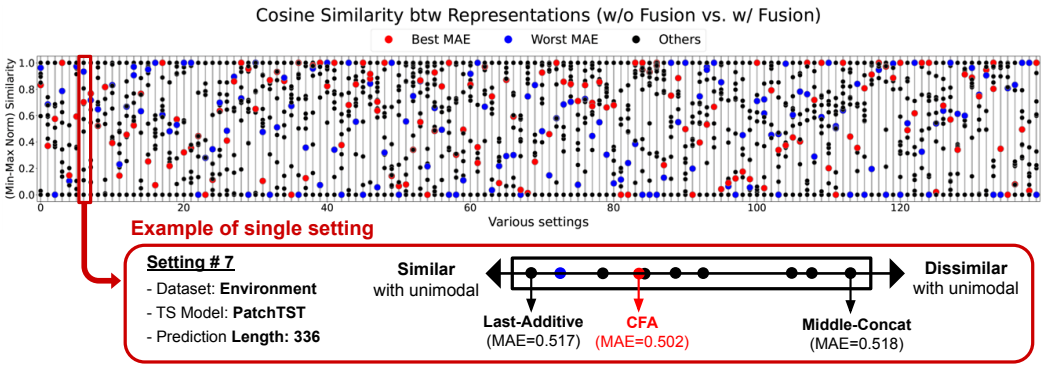
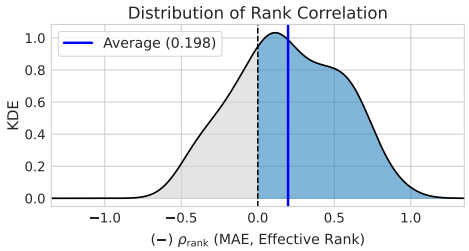


Figure 11: **Cosine similarity between representations of TS-only and TS+Text models.** We apply multiple fusion strategies across diverse settings, where each dot represents a single fusion method. The best-performing method (red) does *not* consistently induce the largest representation shift from the unimodal baseline, highlighting the importance of controlled integration of textual information into temporal representations rather than simply increasing the magnitude of representation shift.

O INFORMATION ANALYSIS

We analyze the fusion using the *effective rank* of layer-wise representations. Given a hidden representation $\mathbf{H}$, we compute its singular values $\{\sigma_i\}_{i=1}^{r}$ and define $p_i = \frac{\sigma_i}{\sum_{j=1}^{r}\sigma_j}$ and $\mathrm{erank}(\mathbf{H}) = \exp\left(-\sum_{i=1}^{r} p_i \log p_i\right)$, where higher rank indicates more distributed representations. To assess its relevance, we compute the rank correlation between MAE and effective rank across fusion strategies under diverse settings (four TS backbones (Liu et al., 2022; Nie et al., 2023; Liu et al., 2024b; Zhou et al., 2022a), nine datasets, four Hs). Figure 12 summarizes the results: Figure 12a shows that methods with higher effective rank tend to achieve lower MAE, as confirmed by a positive Spearman rank correlation, with example shown in Figure 12b.



(a) Distribution of rank correlation.

Method	MAE ↓	Effective Rank ↑
CFA (Ours)	0.0929 (1/11)	24.05 (1/11)
Orthogonal	0.0967 (4/11)	19.37 (3/11)
w/o fusion	0.0970 (5/11)	18.97 (4/11)
Additive (First)	0.0983 (7/11)	16.79 (9/11)
Concat (Middle)	0.0996 (9/11)	16.10 (10/11)
Rank corr. (ρ)	0.6727 (p-value: 0.023)	

(b) Example of rank correlation.

Figure 12: **Rank correlation (MAE, Effective rank).** (a) Distribution of rank correlations across various settings, showing that higher effective rank tends to associate with lower MAE. (b) Methods with higher effective rank generally achieve lower MAE, with rank correlation $\rho = 0.6727$.

P SENSITIVITY ANALYSIS

We examine the robustness of the CFA to the reduction ratio r across datasets and TS models. The results in Table 14 show that performance remains stable for different values of r. Although $r = 4$ achieves the best average performance in several cases, we adopt $r = 8$ in our experiments considering both performance and computational efficiency. For DLinear, FiLM, Koopa, and TSMixer, the adapter acts on the channel dimension, so its width $\max(1, \lfloor C/r \rfloor)$ is small for every r on these low-dimensional datasets, which is why their results are nearly insensitive to r. Tables 15 and 16 report the per-model MAE and MSE, and Tables 17 and 18 the per-dataset values under varying r.

Table 14: Average performance (MAE, MSE) by CFA reduction ratio r.

Metric	$r = 2$	$r = 4$	$r = 8$	$r = 16$	$r = 32$
MAE	1.031	**1.025**	1.029	1.035	1.030
MSE	13.326	**13.290**	13.334	13.374	13.339

Table 15: Average MAE per model by CFA reduction ratio r.

Model	$r = 2$	$r = 4$	$r = 8$	$r = 16$	$r = 32$
Autoformer (Wu et al., 2021)	1.026	1.021	1.031	1.039	**1.018**
Crossformer (Zhang & Yan, 2023)	1.125	1.134	1.127	1.137	**1.118**
DLinear (Zeng et al., 2023)	**0.969**	**0.969**	**0.969**	**0.969**	0.970
FEDformer (Zhou et al., 2022b)	0.967	**0.963**	0.970	0.978	0.981
FiLM (Zhou et al., 2022a)	**0.963**	**0.963**	**0.963**	**0.963**	0.963
Informer (Zhou et al., 2021)	1.217	**1.190**	1.211	1.217	1.208
Koopa (Liu et al., 2023)	**0.944**	**0.944**	**0.944**	**0.944**	0.945
Nonstationary Transformer (Liu et al., 2022)	0.904	0.909	**0.899**	0.916	0.910
PatchTST (Nie et al., 2023)	0.948	**0.943**	0.948	0.948	0.951
Reformer (Kitaev et al., 2020)	1.151	**1.136**	1.167	1.179	1.162
TSMixer (Chen et al., 2023)	**1.123**	**1.123**	**1.123**	**1.123**	**1.123**
TiDE (Das et al., 2023)	0.988	0.979	**0.974**	0.981	0.986
Transformer (Vaswani et al., 2017)	1.149	1.134	**1.128**	1.162	1.145
iTransformer (Liu et al., 2024b)	0.953	0.943	0.950	**0.940**	0.944

Table 16: Average MSE per model by CFA reduction ratio r.

Model	$r = 2$	$r = 4$	$r = 8$	$r = 16$	$r = 32$
Autoformer (Wu et al., 2021)	12.947	**12.744**	13.107	13.203	12.805
Crossformer (Zhang & Yan, 2023)	14.302	14.345	14.135	14.291	**14.088**
DLinear (Zeng et al., 2023)	**12.613**	**12.613**	**12.613**	**12.613**	**12.613**
FEDformer (Zhou et al., 2022b)	**12.597**	12.732	12.748	12.955	12.887
FiLM (Zhou et al., 2022a)	**12.766**	**12.766**	**12.766**	**12.766**	12.766
Informer (Zhou et al., 2021)	14.829	14.851	14.861	14.897	**14.813**
Koopa (Liu et al., 2023)	**12.420**	**12.420**	**12.420**	**12.420**	12.421
Nonstationary Transformer (Liu et al., 2022)	12.247	12.208	**12.185**	12.276	12.274
PatchTST (Nie et al., 2023)	12.615	**12.580**	12.632	12.613	12.584
Reformer (Kitaev et al., 2020)	**14.038**	14.165	14.387	14.447	14.394
TSMixer (Chen et al., 2023)	**14.693**	**14.693**	**14.693**	**14.693**	**14.693**
TiDE (Das et al., 2023)	12.974	**12.756**	12.779	12.797	13.051
Transformer (Vaswani et al., 2017)	14.797	14.714	14.733	**14.691**	14.698
iTransformer (Liu et al., 2024b)	12.727	**12.471**	12.621	12.568	12.654

Table 17: Average MAE per dataset by CFA reduction ratio r.

Dataset	$r = 2$	$r = 4$	$r = 8$	$r = 16$	$r = 32$
Agriculture	0.2534	**0.2452**	0.2508	0.2515	0.2560
Climate	0.8680	0.8655	**0.8648**	0.8669	0.8666
Economy	0.2679	**0.2364**	0.2610	0.2825	0.2518
Energy	0.3927	**0.3894**	0.3908	0.3896	0.3939
Environment	**0.5156**	0.5192	0.5190	0.5188	0.5190
Public Health	0.7976	0.7941	**0.7931**	0.8001	0.7946
Security	5.4168	**5.4129**	5.4218	5.4441	5.4309
Social Good	0.4584	0.4577	**0.4532**	0.4642	0.4545
Traffic	0.3046	0.3054	0.3041	**0.3019**	0.3054

Table 18: Average MSE per dataset by CFA reduction ratio r.

Dataset	$r = 2$	$r = 4$	$r = 8$	$r = 16$	$r = 32$
Agriculture	0.1483	**0.1446**	0.1473	0.1501	0.1526
Climate	1.1596	**1.1520**	1.1537	1.1576	1.1540
Economy	0.1602	**0.1278**	0.1540	0.1790	0.1390
Energy	0.2813	**0.2781**	0.2800	0.2794	0.2838
Environment	**0.4836**	0.4877	0.4875	0.4856	0.4848
Public Health	1.4135	1.4161	**1.4055**	1.4173	1.4062
Security	115.1568	**114.8712**	115.2570	115.5611	115.3047
Social Good	0.9195	0.9183	0.9121	0.9215	**0.9115**
Traffic	0.2114	0.2125	0.2112	**0.2108**	0.2113

Q Statistical Significance and Uncertainty

The main results are reported as averages over a large number of settings, which makes the comparison broad but leaves open whether the differences between strategies are systematic or within run-to-run variation. This section reports the uncertainty and significance analysis behind them.

Setup. We repeat the comparison with 3 random seeds and report the mean and standard deviation of the normalized MSE, aggregated over all settings. Because the per-setting errors are paired (every strategy is evaluated on exactly the same dataset, backbone, text encoder, and horizon) and are not normally distributed across such heterogeneous settings, we use the **Wilcoxon signed-rank test**, a paired non-parametric test, to compare each baseline against CFA. The pairing unit is the setting: for each setting we average the 3 seeds, and the test is run over these per-setting means. As in the main paper, errors are normalized per setting so that datasets with larger scales do not dominate.

Results. Table 19 shows that CFA improves over every baseline at the $p < 0.01$ level, including over the strongest competing constrained strategy (Gating, $p = 0.004$). The standard deviations are small relative to the gaps between methods. For example, the 0.005 spread of Gating is an order of magnitude below its 0.088 gain over the unimodal baseline. The ordering of strategies is therefore stable across seeds, rather than an artifact of a particular run.

Table 19: **Uncertainty and paired significance tests.** Normalized MSE (mean $\pm$ std over 3 seeds) and the p-value of a Wilcoxon signed-rank test of each method against CFA, paired over settings (3-seed mean per setting). Lower is better.

Fusion	Method	Norm. MSE ↓	p vs. CFA
None	Unimodal (w/o fusion)	0.349 ± 0.006	< 0.001
Naive	Additive-Middle (best naive)	0.333 ± 0.007	< 0.001
Constrained	FiLM	0.275 ± 0.005	< 0.001
	Gating	0.261 ± 0.005	0.004
	CFA (Ours)	$\mathbf{0.256 \pm 0.004}$	N/A

Q.1 Rank-Based Comparison across All Settings: Friedman and Nemenyi

The seed-level analysis above addresses run-to-run variability, but it compares aggregated errors. A complementary question is whether the *ordering* of the fusion strategies is consistent across the individual settings, given that error scales differ by orders of magnitude between datasets (from ~ 0.02 on Economy to ~ 100 on Security) and that a few naive-fusion runs diverge outright. We therefore also run the standard non-parametric protocol for comparing multiple methods over multiple datasets (Demšar, 2006): a **Friedman test** followed by a **Nemenyi post-hoc test**. Because these operate on per-setting *ranks*, they are invariant to the scale of each dataset and robust to divergent runs, which makes them well suited to our heterogeneous benchmark.

Protocol. We use the complete per-setting results of Appendix T: $N = 2016$ settings (4 text encoders $\times$ 14 TS backbones $\times$ 9 datasets $\times$ 4 horizons) and $k = 11$ methods (the unimodal baseline, six naive fusion variants, and four constrained fusion strategies). Within each setting the 11 methods are ranked by MSE, with rank 1 assigned to the lowest error and ties resolved by averaging. The Nemenyi critical difference is $\mathrm{CD} = q_\alpha \sqrt{k(k+1)/6N}$, giving $\mathrm{CD} = 0.336$ at $\alpha = 0.05$ and $\mathrm{CD} = 0.386$ at $\alpha = 0.01$. Two methods differ significantly when their average ranks differ by more than the corresponding CD.

Results. The Friedman test rejects the null hypothesis that all 11 methods perform equivalently, with $\chi^2(10) = 1930.4$ and $p \approx 2.4 \times 10^{-409}$ (Iman–Davenport $F(10, 20150) = 213.4$, same conclusion). Table 20 reports the average ranks and the post-hoc comparisons against CFA, and Figure 13 shows the corresponding critical-difference diagram, from which four points follow.

Table 20: **Friedman average ranks and Nemenyi post-hoc tests over all $N = 2016$ settings** ($k = 11$ methods, where rank 1 denotes the lowest MSE and lower is better). Δ is the rank gap to CFA, and a gap exceeding $\mathrm{CD}_{0.05} = 0.336$ (resp. $\mathrm{CD}_{0.01} = 0.386$) is significant at that level. Win/Tie/Loss counts settings in which CFA is better / equal / worse, with the corresponding paired Wilcoxon signed-rank p-value.

Fusion	Method	Avg. rank ↓	Δ vs. CFA	Nemenyi p	CFA Win/Tie/Loss	Wilcoxon p
Constrained	**CFA (Ours)**	**4.473**	N/A	N/A	N/A	N/A
Constrained	Gating	4.834	0.361	0.023	1049 / 96 / 871	8.6×10^{-7}
	FiLM	5.391	0.918	$< 10^{-15}$	1139 / 83 / 794	8.5×10^{-14}
	Orthogonal	5.585	1.112	$< 10^{-15}$	1232 / 103 / 681	7.8×10^{-31}
None	Unimodal (w/o fusion)	5.411	0.938	$< 10^{-15}$	1204 / 127 / 685	2.5×10^{-40}
Naive	Additive-Middle	6.012	1.539	$< 10^{-15}$	1295 / 72 / 649	8.9×10^{-41}
	Additive-Last	6.079	1.606	$< 10^{-15}$	1323 / 35 / 658	1.0×10^{-49}
	Concat-Middle	6.169	1.696	$< 10^{-15}$	1256 / 57 / 703	7.8×10^{-45}
	Additive-First	7.095	2.622	$< 10^{-15}$	1422 / 60 / 534	1.8×10^{-104}
	Concat-First	7.127	2.654	$< 10^{-15}$	1384 / 45 / 587	1.3×10^{-92}
	Concat-Last	7.822	3.349	$< 10^{-15}$	1511 / 7 / 498	2.9×10^{-161}

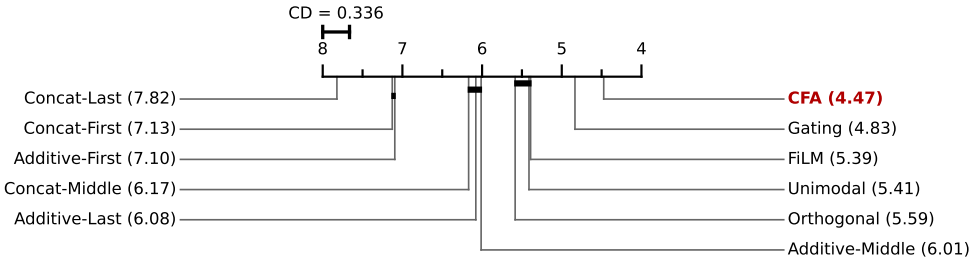


Figure 13: **Critical-difference diagram** (Nemenyi, $\alpha = 0.05$, $N = 2016$ settings). Methods are positioned by average rank, lower (further right) is better. Methods connected by a bold horizontal bar are *not* significantly different from one another. No bar reaches CFA, i.e., CFA is significantly better than every other strategy.

(i) CFA attains the best average rank (4.473) among all 11 methods, and its gap to every competitor exceeds $\mathrm{CD}_{0.05}$. CFA is therefore significantly better than each of the ten alternatives at $\alpha = 0.05$, and at $\alpha = 0.01$ against all except Gating. No clique bar reaches CFA in Figure 13.

(ii) Naive fusion ranks below the unimodal baseline. The unimodal baseline attains rank 5.411, better than *all six* naive fusion variants (6.01–7.82). Adding text through an unconstrained operator is thus not merely unhelpful on average. It is worse than not adding text at all. This holds under a scale-free rank comparison over 2016 settings, and not only in the aggregated means of Table 4. Middle-layer fusion ranks above first-layer fusion for both operators, and concatenation ranks below addition at every position, consistent with Section 4.2.

(iii) Only constrained fusion outranks the unimodal baseline. Three of the four constrained strategies (CFA, Gating, FiLM) rank above it, while Orthogonal (5.585) falls slightly below. This is consistent with the main text, where Orthogonal is also the weakest constrained variant. Being constrained is therefore necessary but not sufficient, and the specific form of the constraint matters.

(iv) The rank analysis and the seed analysis agree. The ordering in Table 20 matches that of Table 19, and Gating is in both analyses the closest competitor and the only one for which the margin, while significant, is modest. The two tests differ in what they control for. One accounts for seed variability on aggregated normalized errors, and the other uses scale-free per-setting ranks. Their agreement indicates that the conclusion is not an artifact of either aggregation choice.

The improvements are robust to how they are measured. Three properties of the main results support this beyond the p-values above.

(i) Gains are not optimization artifacts. Every setting is tuned over 10 learning rates and the best result is compared, so a difference between strategies cannot be attributed to one method being better tuned than another (Section 4.2).

(ii) Wins are broad, not concentrated. CFA beats the unimodal baseline on $9/9$ datasets and $13/14$ backbones, and ranks first among the 10 fusion strategies on $7/9$ datasets (Figure 3a, Figure 3b). A method that won by a small margin on a few favorable settings would not produce this pattern.

(iii) Significance is also established in the controlled analyses. The representation study reports a two-sample t-test with $t = 4.03$, $p < 0.001$ and Cohen's $d = 0.58$ (Appendix J.2), and the rank-correlation analysis reports $\rho = 0.6727$ with $p = 0.023$ (Appendix O).

On the magnitude of the improvements. The absolute margins in Table 4 are modest in the way that is typical of this literature. This is a property of the task rather than of our method: the premise of multimodal TS forecasting is that text is auxiliary and *may* help, so the meaningful question is whether a fusion strategy improves on the unimodal baseline at all, and how often. This is why we report win rates against the unimodal baseline alongside averages, and why the complete per-setting results are provided in Appendix T rather than only summary statistics. Measured on that axis, the gap between constrained and naive fusion is large: even the best naive strategy ranks significantly below doing nothing, whereas CFA ranks significantly above it and improves on it in 1204 of the 2016 settings (about 60%).

R GENERALIZATION TO A TEXT-PAIRED ETT BENCHMARK

This section reports a generalization study on ETT, a widely used TS forecasting benchmark that lies outside the Time-MMD collection used in the main paper.

R.1 MOTIVATION AND CONSTRUCTION OF A TEXT-PAIRED ETT

All experiments in the main paper use Time-MMD (Liu et al., 2024a), currently the largest public collection of paired text–TS data. A natural question is whether our conclusions depend on that benchmark. Answering it on a standard benchmark such as ETT is not immediate: **ETT is a purely unimodal dataset**, containing only sensor channels (oil temperature `OT` and six load features) with *no* accompanying text, so the multimodal setting studied here is not defined on it out of the box.

We therefore *construct* a paired text channel for ETT, following the way prior LLM-based TS methods attach text to purely numerical series. We adopt the *prompt-as-prefix* scheme of Time-LLM (Jin et al., 2024), which renders dataset context and input statistics into a natural-language prompt.

Construction procedure. For every time index t, we build a short description of the recent behavior of the series using **only values strictly before** t:

1. Take the trailing window of the target `OT` channel ending just before t, of length equal to the lookback L.
2. From that window compute the most recent few values, the **trend** (rose / fell / flat, determined by a first-versus-last comparison with a volatility-based tolerance), the **percent change**, the **mean**, the **volatility** (standard deviation), and the **current level relative to the recent average** (above / near / below).
3. Render these into a single natural-language sentence. A real sample reads:

   > *"Recent oil temperature (OT) readings were: 25.18, 30.53, 27.65, 25.47. Over the last 96 steps the value fell from 30.53 to 25.47 (change -16.6%), with mean 24.23 and volatility 4.25. The current level is near its recent average."*

4. Pair the sentence with the input window, so that the model reads the text at the end of the lookback window.

Because the text at t depends only on values strictly before t, **no information about the forecast horizon leaks through the text channel**, consistent with the formulation in Section 3 and the discussion in Appendix G.1.

Protocol. Text is encoded with a frozen BERT encoder (Devlin et al., 2019), and every setting is evaluated under the protocol of the main paper (best result over the learning-rate sweep). The sweep covers **4 datasets** (ETTh1, ETTh2, ETTm1, ETTm2) $\times$ **3 backbones** (PatchTST, DLinear, iTransformer) $\times$ **2 input lengths** $L \in \{96, 336\}$ $\times$ **4 horizons** $H \in \{96, 192, 336, 720\}$, giving **96 settings**. We stress that this text is *weak by construction*: it is derived from the series itself and carries no exogenous information, so it is a conservative test of whether constrained fusion remains safe when the auxiliary signal is uninformative.

R.2 Results: Naive Fusion Fails, Constrained Fusion Does Not

Table 21 averages over all 96 settings. The pattern reported on Time-MMD reproduces on ETT.

Table 21: **Text-paired ETT: average over all 96 settings.** Improv. is the relative reduction with respect to the unimodal baseline. Win/Loss counts the settings in which a method beats or loses to the unimodal baseline, out of 96.

Fusion	Method	Avg MSE ↓	MSE Improv. (%)	Avg MAE ↓	MAE Improv. (%)	Win/Loss
None	Unimodal (TS-only)	0.1920	N/A	0.3225	N/A	N/A
Naive	Additive-Middle	0.1918	$+0.11$	0.3237	-0.35	50 / 46
	Additive-Last	0.1930	-0.51	0.3240	-0.45	42 / 54
	Concat-First	0.1980	-3.14	0.3298	-2.24	35 / 61
Constrained	Gating	0.1942	-1.14	0.3262	-1.14	43 / 53
	CFA (Ours)	**0.1893**	$\mathbf{+1.42}$	**0.3207**	$\mathbf{+0.56}$	**57 / 39**

Four observations follow.

(i) Every naive fusion variant fails to reliably beat the unimodal model. Concat-First *degrades* it by 3.14% MSE while winning only 35 of 96 settings, Additive-Last by 0.51%, and Additive-Middle is a statistical wash ($+0.11\%$, $50/46$). This reproduces on an entirely different benchmark the instability we report on Time-MMD (Figure 1, Table 4).

(ii) Being constrained is not by itself sufficient. Gating, although a constrained strategy, still underperforms the unimodal baseline (-1.14%), mirroring the main-paper finding that constrained fusion strategies can also fall below the unimodal model in certain settings. Robustness is a property of the specific constraint, not of the category.

(iii) CFA is the only method that consistently improves over the unimodal baseline ($+1.42\%$ MSE, $+0.56\%$ MAE, $57/39$ win/loss). It attains the lowest average MSE on **all four** datasets (Table 22), which is the same ranking as in the main experiments (Figure 3a).

(iv) Gains grow with the horizon. The improvement is slightly negative at $H = 96$ and $H = 192$ (-0.9% and -0.6%) and rises to $+2.0\%$ at $H = 336$ and $+3.4\%$ at $H = 720$, i.e., precisely where forecasting is hardest and contextual information is most valuable.

Table 22: **Text-paired ETT: per-dataset average MSE.** CFA attains the lowest error everywhere.

Dataset	Unimodal	Additive-Middle	Additive-Last	Concat-First	Gating	**CFA (Ours)**
ETTh1	0.1266	0.1256	0.1277	0.1300	0.1250	**0.1240**
ETTh2	0.3208	0.3230	0.3238	0.3284	0.3275	**0.3174**
ETTm1	0.0919	0.0913	0.0923	0.0988	0.0917	**0.0902**
ETTm2	0.2286	0.2271	0.2280	0.2347	0.2325	**0.2255**

R.3 Full Per-Setting Results

Tables 23 and 24 report every one of the 96 settings separately, with each input length L and horizon H broken out. Per-setting gains reach $+13.24\%$ MSE (ETTh2 / PatchTST / $L = 336$, $H = 720$) and $+11.00\%$ (ETTh1 / PatchTST / $L = 96$, $H = 336$).

Taken together, the ETT study supports the central claim of the paper on a benchmark that was never designed for multimodal use and whose text is deliberately weak: *naive fusion is unreliable, while low-rank constrained fusion safely improves a strong unimodal forecaster*.

Table 23: **Text-paired ETT (hourly): full per-setting comparison of the unimodal baseline and CFA.** Improv. is the relative reduction of CFA over the unimodal baseline. Positive favours CFA.

Model	L	H	MSE			MAE		
			Unimodal	CFA	Improv. (%)	Unimodal	CFA	Improv. (%)
ETTh1								
PatchTST	96	96	0.1063	0.1059	+0.38	0.2494	0.2469	+0.98
		192	0.1362	0.1281	+5.99	0.2827	0.2745	+2.89
		336	0.1536	0.1367	+11.00	0.3060	0.2884	+5.77
		720	0.1924	0.1729	+10.12	0.3476	0.3289	+5.40
	336	96	0.0935	0.0945	−1.08	0.2345	0.2381	−1.51
		192	0.1134	0.1153	−1.75	0.2635	0.2642	−0.25
		336	0.1273	0.1215	+4.52	0.2809	0.2756	+1.91
		720	0.1798	0.1713	+4.70	0.3346	0.3265	+2.43
DLinear	96	96	0.1062	0.1063	−0.10	0.2495	0.2500	−0.19
		192	0.1244	0.1243	+0.12	0.2706	0.2704	+0.08
		336	0.1254	0.1253	+0.05	0.2757	0.2764	−0.26
		720	0.1412	0.1395	+1.17	0.3020	0.2983	+1.21
	336	96	0.0929	0.0944	−1.58	0.2369	0.2397	−1.19
		192	0.1031	0.1027	+0.39	0.2501	0.2502	−0.05
		336	0.1074	0.1092	−1.70	0.2582	0.2607	−1.00
		720	0.1295	0.1299	−0.29	0.2917	0.2920	−0.10
iTransformer	96	96	0.1075	0.1084	−0.83	0.2481	0.2510	−1.18
		192	0.1321	0.1312	+0.70	0.2782	0.2765	+0.60
		336	0.1327	0.1335	−0.64	0.2835	0.2827	+0.26
		720	0.1633	0.1635	−0.18	0.3198	0.3208	−0.31
	336	96	0.0966	0.0987	−2.15	0.2409	0.2440	−1.28
		192	0.1105	0.1091	+1.27	0.2599	0.2543	+2.15
		336	0.1249	0.1141	+8.66	0.2772	0.2655	+4.24
		720	0.1387	0.1393	−0.48	0.3024	0.3038	−0.47
Average			**0.1266**	**0.1240**	**+2.08**	**0.2768**	**0.2741**	**+0.97**
ETTh2								
PatchTST	96	96	0.2575	0.2610	−1.34	0.3836	0.3893	−1.49
		192	0.3045	0.2927	+3.87	0.4352	0.4244	+2.50
		336	0.3325	0.3283	+1.26	0.4591	0.4532	+1.28
		720	0.4656	0.4632	+0.53	0.5445	0.5411	+0.63
	336	96	0.2420	0.2456	−1.49	0.3778	0.3773	+0.15
		192	0.3179	0.3451	−8.57	0.4484	0.4663	−3.99
		336	0.3956	0.3824	+3.33	0.5027	0.4995	+0.63
		720	0.4725	0.4099	+13.24	0.5510	0.5146	+6.61
DLinear	96	96	0.2622	0.2740	−4.51	0.3905	0.4022	−3.00
		192	0.3094	0.3064	+0.95	0.4335	0.4310	+0.57
		336	0.3323	0.3295	+0.84	0.4517	0.4494	+0.53
		720	0.3962	0.3924	+0.96	0.4984	0.4956	+0.55
	336	96	0.2368	0.2411	−1.81	0.3805	0.3853	−1.26
		192	0.2797	0.2788	+0.32	0.4229	0.4236	−0.16
		336	0.3070	0.3052	+0.60	0.4437	0.4429	+0.18
		720	0.3682	0.3667	+0.41	0.4875	0.4865	+0.20
iTransformer	96	96	0.2685	0.2635	+1.88	0.3894	0.3858	+0.93
		192	0.3193	0.3173	+0.62	0.4368	0.4386	−0.42
		336	0.3403	0.3369	+0.99	0.4559	0.4546	+0.28
		720	0.3974	0.3811	+4.10	0.4984	0.4881	+2.07
	336	96	0.2423	0.2444	−0.87	0.3812	0.3834	−0.58
		192	0.2590	0.2664	−2.84	0.4039	0.4032	+0.16
		336	0.2826	0.2844	−0.62	0.4250	0.4277	−0.63
		720	0.3091	0.3016	+2.42	0.4432	0.4365	+1.49
Average			**0.3208**	**0.3174**	**+1.05**	**0.4435**	**0.4417**	**+0.42**

Table 24: **Text-paired ETT (minute-level): full per-setting comparison of the unimodal baseline and CFA.** Improv. is the relative reduction of CFA over the unimodal baseline. Positive favours CFA.

Model	L	H	MSE			MAE		
			Unimodal	CFA	Improv. (%)	Unimodal	CFA	Improv. (%)
ETTm1								
PatchTST	96	96	0.0446	0.0447	−0.22	0.1521	0.1524	−0.22
		192	0.0749	0.0740	+1.25	0.2047	0.2025	+1.07
		336	0.1117	0.1011	+9.48	0.2538	0.2405	+5.22
		720	0.1505	0.1362	+9.51	0.2955	0.2819	+4.59
	336	96	0.0438	0.0445	−1.63	0.1534	0.1576	−2.75
		192	0.0735	0.0715	+2.78	0.2019	0.1988	+1.53
		336	0.1012	0.1009	+0.34	0.2411	0.2373	+1.56
		720	0.1287	0.1313	−2.05	0.2731	0.2757	−0.97
DLinear	96	96	0.0458	0.0455	+0.66	0.1528	0.1523	+0.32
		192	0.0745	0.0748	−0.38	0.2005	0.2010	−0.22
		336	0.1086	0.1084	+0.20	0.2460	0.2460	−0.03
		720	0.1475	0.1459	+1.06	0.2944	0.2918	+0.88
	336	96	0.0460	0.0453	+1.34	0.1571	0.1560	+0.71
		192	0.0718	0.0719	−0.03	0.2010	0.2015	−0.22
		336	0.0993	0.1007	−1.47	0.2394	0.2419	−1.04
		720	0.1256	0.1258	−0.14	0.2715	0.2712	+0.09
iTransformer	96	96	0.0461	0.0458	+0.74	0.1541	0.1529	+0.77
		192	0.0771	0.0806	−4.49	0.2036	0.2080	−2.16
		336	0.1176	0.1101	+6.32	0.2556	0.2451	+4.09
		720	0.1513	0.1390	+8.16	0.2951	0.2832	+4.04
	336	96	0.0498	0.0479	+3.75	0.1622	0.1599	+1.44
		192	0.0794	0.0823	−3.64	0.2106	0.2124	−0.86
		336	0.1073	0.1071	+0.16	0.2487	0.2458	+1.17
		720	0.1301	0.1292	+0.71	0.2754	0.2722	+1.16
Average			**0.0919**	**0.0902**	**+1.91**	**0.2227**	**0.2203**	**+1.04**
ETTm2								
PatchTST	96	96	0.1133	0.1114	+1.73	0.2313	0.2302	+0.48
		192	0.1860	0.1819	+2.19	0.3104	0.3091	+0.41
		336	0.2788	0.2649	+4.98	0.3882	0.3841	+1.07
		720	0.3724	0.3553	+4.57	0.4645	0.4605	+0.85
	336	96	0.1154	0.1161	−0.62	0.2447	0.2459	−0.49
		192	0.1807	0.1770	+2.01	0.3173	0.3104	+2.17
		336	0.2447	0.2528	−3.30	0.3745	0.3807	−1.65
		720	0.2983	0.2909	+2.49	0.4197	0.4204	−0.17
DLinear	96	96	0.1221	0.1223	−0.13	0.2426	0.2418	+0.33
		192	0.1843	0.1857	−0.76	0.3093	0.3109	−0.51
		336	0.2666	0.2620	+1.70	0.3783	0.3767	+0.42
		720	0.3530	0.3525	+0.14	0.4517	0.4517	−0.00
	336	96	0.1218	0.1184	+2.79	0.2480	0.2442	+1.50
		192	0.1812	0.1846	−1.90	0.3128	0.3175	−1.49
		336	0.2492	0.2499	−0.30	0.3763	0.3765	−0.05
		720	0.3088	0.3077	+0.34	0.4298	0.4289	+0.20
iTransformer	96	96	0.1210	0.1231	−1.72	0.2356	0.2411	−2.31
		192	0.2002	0.2028	−1.28	0.3239	0.3260	−0.65
		336	0.2955	0.2747	+7.02	0.3964	0.3821	+3.61
		720	0.3826	0.3514	+8.16	0.4729	0.4605	+2.62
	336	96	0.1246	0.1311	−5.20	0.2513	0.2635	−4.84
		192	0.1951	0.2071	−6.17	0.3261	0.3344	−2.54
		336	0.2679	0.2682	−0.14	0.3877	0.3911	−0.86
		720	0.3234	0.3195	+1.20	0.4388	0.4355	+0.76
Average			**0.2286**	**0.2255**	**+1.38**	**0.3472**	**0.3468**	**+0.10**

S Comparison with Other Methods

Table 25 presents a comparison of our method against other TS models, covering both unimodal TS models and architecture-specific multimodal TS models. We use eight Time-MMD multimodal datasets (Liu et al., 2024a), excluding the Environment dataset due to reproducibility issues with the baseline methods.[2] The results are based on SpecTF (Nguyen et al., 2026), which is concurrent with our work (2026.02). We apply our approach to three representative TS backbones: a Transformer-based model (Nonstationary Transformer (Liu et al., 2022)), a Linear/MLP-based model (TiDE (Das et al., 2023)), and other architectures (Koopa (Liu et al., 2023)).

Table 25: **Comparison with other methods, including architecture-specific multimodal TS forecasting models. Red bold**: best, blue underline: second best.

Dataset	H	SpecTF (Nguyen et al., 2026)	TaTS (Li et al., 2025)	MM-TSF (Liu et al., 2024a)	TimeXer (Wang et al., 2024)	FreTS (Yi et al., 2023)	Time-LLM (Jin et al., 2024)	ChatTime (Wang et al., 2025)	**CFA** (Ours) + Transformer (Liu et al., 2022)	**CFA** (Ours) + Linear/MLP (Das et al., 2023)	**CFA** (Ours) + Others (Liu et al., 2023)
Agriculture	6	0.064	0.075	0.084	0.088	0.082	0.092	0.193	**0.053**	0.060	0.056
	8	0.084	0.097	0.112	0.109	0.101	0.151	0.264	**0.069**	0.082	0.076
	10	0.110	0.127	0.133	0.144	0.125	0.176	0.345	**0.091**	0.103	0.100
	12	0.152	0.167	0.165	0.187	0.172	0.210	0.418	**0.116**	0.135	0.128
	Avg	0.103	0.117	0.123	0.132	0.120	0.157	0.305	**0.082**	0.095	0.090
Climate	6	**0.904**	0.990	1.074	1.027	1.286	1.126	1.490	1.073	1.258	1.253
	8	**0.927**	0.998	1.067	1.059	1.283	1.165	1.530	1.250	1.267	1.258
	10	**0.965**	1.010	1.100	1.067	1.294	1.200	1.519	1.176	1.259	1.247
	12	**0.960**	1.012	1.101	1.058	1.293	1.210	1.570	1.163	1.274	1.232
	Avg	**0.938**	1.002	1.053	1.053	1.289	1.175	1.528	1.166	1.265	1.248
Economy	6	0.0084	**0.0080**	0.0116	0.0133	0.0150	0.0307	0.0478	0.017	0.017	0.017
	8	0.0086	**0.0083**	0.0117	0.0140	0.0149	0.0310	0.056	0.020	0.018	0.018
	10	0.0085	**0.0083**	0.0126	0.0143	0.0155	0.0323	0.056	0.019	0.017	0.017
	12	0.0086	**0.0084**	0.0125	0.0148	0.0154	0.0336	0.059	0.020	0.017	0.018
	Avg	0.0085	**0.0083**	0.0121	0.0141	0.0152	0.0319	0.0547	0.019	0.017	0.018
Energy	12	**0.096**	0.103	0.117	0.137	0.127	0.105	0.135	0.101	0.112	0.107
	24	0.199	0.206	0.210	0.242	0.245	0.216	0.238	**0.186**	0.220	0.205
	36	**0.282**	0.313	0.307	0.324	0.337	0.307	0.328	0.306	0.300	0.299
	48	0.406	0.433	0.447	0.447	0.487	0.427	0.435	0.404	0.408	**0.402**
	Avg	**0.246**	0.264	0.270	0.288	0.299	0.264	0.284	0.249	0.260	0.253
Public Health	12	0.985	0.979	1.196	1.181	1.141	1.308	1.382	**0.724**	1.106	1.008
	24	1.256	1.297	1.440	1.402	1.546	1.724	1.758	**1.032**	1.425	1.410
	36	1.395	1.442	1.669	1.455	1.691	1.869	1.904	**1.371**	1.602	1.625
	48	1.470	1.519	1.755	1.538	1.790	1.895	1.930	**1.269**	1.740	1.715
	Avg	1.276	1.340	1.508	1.394	1.542	1.699	1.730	**1.099**	1.468	1.440
Security	6	106.364	108.460	113.759	106.859	126.132	106.535	113.701	**99.239**	107.5	104.5
	8	106.947	110.180	115.563	109.134	129.167	108.205	117.083	**105.3**	109.4	105.5
	10	109.767	111.352	116.793	110.484	129.848	109.566	123.805	**107.8**	111.9	108.7
	12	110.567	112.405	117.897	111.411	130.346	110.865	190.503	109.7	111.7	**109.4**
	Avg	108.4	110.6	116.0	109.5	128.9	108.8	136.273	**105.5**	110.1	107.0
Social Good	6	0.907	0.943	1.088	0.924	1.008	0.888	1.193	**0.793**	0.843	0.849
	8	0.939	1.012	1.183	0.978	1.017	0.916	1.117	**0.897**	0.947	0.914
	10	0.962	0.996	1.198	1.018	1.145	1.039	1.241	**0.928**	1.068	0.994
	12	1.040	1.058	1.264	1.089	1.174	1.492	1.189	**1.020**	1.147	1.079
	Avg	0.962	1.012	1.183	1.002	1.086	1.084	1.185	**0.910**	1.001	0.959
Traffic	6	0.169	0.182	0.186	**0.166**	0.200	0.271	0.255	0.172	0.233	0.196
	8	0.169	0.184	0.190	**0.167**	0.199	0.276	0.257	0.180	0.224	0.207
	10	**0.173**	0.190	0.195	0.176	0.205	0.279	0.259	0.187	0.229	0.209
	12	**0.175**	0.213	0.217	0.197	0.215	0.333	0.261	0.243	0.289	0.269
	Avg	**0.171**	0.192	0.197	0.176	0.205	0.289	0.258	0.196	0.244	0.220

[2]The reproducibility issue with Environment arises in MM-TSF (Liu et al., 2024a), which corresponds to the last-additive setting in our experiments, and the reported results differ from those obtained in our runs.

T FULL RESULTS OF MAIN EXPERIMENTS

This section reports the complete per-setting results that underlie the aggregated comparison of Table 4 in the main paper. For each text encoder (**BERT**, **GPT-2**, **Llama-3**, and **Doc2Vec**), we provide one table per TS backbone (14 backbones in total), covering all 9 datasets and 4 forecasting horizons ($H \in \{6, 8, 10, 12\}$ for monthly, $\{12, 24, 36, 48\}$ for weekly, and $\{48, 96, 192, 336\}$ for daily). Each table contrasts the unimodal baseline against six naive fusion variants (Additive/Concat at First/Middle/Last layers) and four constrained methods (Orthogonal, FiLM, Gating, CFA).

Text Model: BERT. The following tables present the BERT-based multimodal forecasting results across all 14 TS backbones. For each backbone, the table reports the unimodal MSE alongside the multimodal variants obtained by fusing BERT embeddings with all ten fusion strategies.

Table 26: Multimodal fusion strategies with **Nonstationary Transformer** (+ **BERT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	CFA
Nonstationary Transformer	Agriculture	6	0.055	0.061	**0.050**	**0.052**	0.062	**0.054**	1.746	**0.051**	**0.053**	0.058	**0.053**
		8	0.071	0.073	**0.070**	**0.068**	0.073	**0.070**	1.026	**0.070**	**0.070**	0.074	**0.067**
		10	0.092	0.102	**0.090**	**0.088**	0.100	**0.091**	0.367	**0.092**	**0.092**	**0.090**	**0.092**
		12	0.116	0.121	0.119	**0.110**	0.127	0.120	0.428	0.121	0.126	0.118	0.116
	Climate	6	1.206	1.316	1.302	**1.192**	**1.106**	1.237	1.296	1.304	**1.179**	1.226	**1.084**
		8	1.240	1.301	**1.128**	**1.232**	1.248	1.302	**1.154**	1.286	**1.238**	**1.203**	1.246
		10	1.283	1.296	**1.281**	**1.224**	**1.248**	**1.150**	**1.078**	**1.246**	**1.211**	1.297	**1.192**
		12	1.262	**1.237**	**1.205**	**1.193**	**1.257**	**1.231**	**1.083**	**1.221**	**1.203**	**1.203**	**1.156**
	Economy	6	0.016	0.018	0.018	0.017	0.017	**0.016**	7.850	0.018	0.017	0.018	0.017
		8	0.018	0.019	0.019	0.020	0.020	0.019	8.342	0.018	0.019	0.019	0.019
		10	0.020	0.020	**0.019**	0.023	0.021	0.021	1.054	0.021	0.020	0.023	**0.019**
		12	0.020	0.022	0.022	**0.020**	0.023	0.020	1.001	0.020	**0.020**	0.021	**0.020**
	Energy	12	0.106	0.115	**0.104**	**0.093**	**0.085**	**0.094**	0.178	**0.102**	**0.104**	**0.098**	**0.105**
		24	0.159	0.202	0.177	0.209	0.207	0.220	0.595	0.195	0.209	0.206	0.231
		36	0.333	**0.297**	**0.303**	**0.313**	**0.297**	**0.292**	0.927	**0.298**	**0.295**	**0.273**	**0.299**
		48	0.391	0.459	0.441	0.413	0.420	0.402	0.586	**0.366**	**0.362**	0.398	**0.342**
	Environment	48	0.430	0.436	0.446	0.437	0.448	0.432	0.448	0.436	**0.426**	0.431	0.430
		96	0.433	0.477	0.457	0.441	**0.422**	0.461	0.451	0.455	0.446	0.441	0.438
		192	0.445	0.500	0.454	**0.444**	0.462	0.488	0.461	**0.434**	**0.431**	0.479	**0.423**
		336	0.438	0.499	**0.430**	**0.427**	0.455	**0.431**	0.484	**0.436**	0.440	**0.437**	0.476
	Public Health	12	0.841	**0.793**	**0.819**	0.940	**0.821**	0.891	1.143	**0.830**	**0.800**	**0.714**	**0.714**
		24	1.160	1.174	**0.954**	1.214	**1.108**	1.294	1.662	1.181	1.374	1.212	**1.030**
		36	1.247	**1.208**	**1.241**	1.292	1.456	1.461	1.473	1.380	1.515	1.339	1.276
		48	1.593	1.720	**1.552**	**1.258**	1.697	**1.312**	**1.584**	**1.549**	**1.449**	**1.347**	**1.323**
	Security	6	103.4	**102.4**	105.9	105.6	**101.3**	106.0	121.3	**101.4**	**100.7**	**102.6**	**100.3**
		8	104.9	105.7	107.5	106.9	106.0	**104.7**	124.7	**104.5**	**103.5**	**104.1**	**104.8**
		10	107.8	108.0	107.9	108.2	**107.5**	108.0	122.5	**107.7**	108.4	108.3	108.5
		12	109.3	109.5	109.8	**109.0**	109.5	109.5	117.3	**109.2**	**108.7**	109.6	109.6
	Social Good	6	0.790	0.806	0.791	**0.750**	0.832	**0.770**	4.429	0.801	0.829	0.793	0.798
		8	0.908	0.945	**0.884**	0.911	1.021	**0.871**	2.870	0.953	**0.905**	**0.884**	**0.893**
		10	0.996	**0.966**	**0.969**	**0.925**	1.060	**0.973**	1.092	1.072	**0.928**	**0.952**	**0.926**
		12	1.073	**1.045**	**1.027**	**0.988**	1.089	**1.025**	**1.056**	1.147	**1.068**	**1.072**	**1.022**
	Traffic	6	0.182	**0.173**	**0.182**	0.191	0.186	**0.172**	0.616	0.185	0.188	**0.175**	**0.173**
		8	0.185	0.190	0.188	0.201	0.195	0.186	0.546	0.191	0.186	**0.184**	**0.185**
		10	0.187	**0.186**	**0.182**	0.192	0.190	**0.177**	0.252	0.190	**0.182**	0.192	0.188
		12	0.243	0.255	0.251	0.257	**0.235**	**0.240**	0.262	0.244	0.248	**0.242**	**0.242**

Table 27: Multimodal fusion strategies with **Koopa** (+ **BERT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	CFA
Koopa	Agriculture	6	0.059	**0.057**	**0.058**	**0.058**	3.581	1.539	1.539	0.061	0.072	**0.057**	**0.056**
		8	0.077	**0.070**	**0.071**	**0.071**	0.188	0.187	0.187	0.077	0.129	**0.074**	**0.076**
		10	0.099	**0.092**	**0.090**	**0.090**	1.280	0.406	0.406	0.100	0.118	**0.091**	0.100
		12	0.129	**0.118**	**0.118**	**0.118**	0.799	0.662	0.662	0.130	0.174	**0.117**	**0.129**
	Climate	6	1.251	14.469	1.255	1.255	6.592	**1.219**	**1.219**	1.268	**1.079**	**1.246**	1.253
		8	1.264	1.541	1.267	1.267	**1.195**	**1.114**	**1.114**	1.320	**1.072**	1.268	**1.258**
		10	1.247	3.619	1.254	1.254	1.426	**1.053**	**1.053**	1.299	**1.115**	**1.246**	1.247
		12	1.232	1.248	1.251	1.251	**1.195**	**1.202**	**1.202**	1.249	**1.084**	1.249	1.232
	Economy	6	0.021	0.037	0.026	0.026	11.634	11.957	11.957	0.030	0.054	0.023	**0.017**
		8	0.017	0.019	0.019	0.019	0.739	0.796	0.796	0.023	0.034	0.018	0.018
		10	0.017	0.025	0.021	0.021	4.070	3.392	3.392	0.028	0.053	**0.017**	**0.017**
		12	0.018	0.030	0.029	0.029	13.558	14.694	14.694	0.029	0.063	0.025	0.018
	Energy	12	0.107	7203.5	**0.107**	**0.107**	195.3	0.162	0.162	0.115	0.111	0.110	0.107
		24	0.216	0.296	**0.205**	**0.205**	988.7	0.394	0.394	0.218	**0.213**	**0.196**	**0.205**
		36	0.300	**0.299**	**0.293**	**0.293**	0.681	0.504	0.504	0.314	0.309	**0.297**	**0.299**
		48	0.388	22512.6	0.404	0.404	31.815	1.075	1.075	0.434	0.414	**0.385**	0.402
	Environment	48	0.482	1124061696.0	**0.457**	**0.457**	237790768.0	**0.442**	**0.442**	0.487	**0.462**	**0.464**	**0.481**
		96	0.526	1906434688.0	**0.473**	**0.473**	0.954	**0.444**	**0.444**	0.539	**0.456**	**0.484**	0.533
		192	0.567	4849368576.0	**0.526**	**0.526**	39476484.0	**0.498**	**0.498**	**0.567**	**0.498**	**0.526**	**0.564**
		336	0.528	1709358592.0	0.531	0.531	593.9	**0.495**	**0.495**	0.529	**0.515**	**0.510**	0.528
	Public Health	12	1.029	1956.1	**0.940**	**0.940**	113.8	**0.941**	**0.941**	1.343	1.301	**0.908**	**1.008**
		24	1.395	**1.190**	**1.139**	**1.139**	1.827	**1.221**	**1.221**	1.582	**1.380**	**1.164**	1.410
		36	1.614	**1.243**	**1.285**	**1.285**	2.072	1.626	1.626	1.738	**1.302**	**1.272**	1.625
		48	1.729	**1.530**	**1.374**	**1.374**	2.099	1.736	1.736	1.885	**1.487**	**1.362**	**1.715**
	Security	6	104.9	**97.303**	**103.8**	**103.8**	136.5	138.2	138.2	**103.0**	108.8	**103.6**	**104.5**
		8	109.1	120.2	**108.8**	**108.8**	**108.2**	110.5	110.5	112.9	114.3	**104.6**	**105.5**
		10	108.8	**105.3**	**107.6**	**107.6**	117.7	116.7	116.7	109.8	111.0	**108.7**	**108.7**
		12	111.3	**109.8**	**110.1**	**110.1**	158.0	160.8	160.8	114.6	113.1	**109.7**	**109.4**
	Social Good	6	0.847	0.848	0.871	0.871	3.168	3.427	3.427	0.881	**0.753**	**0.830**	0.851
		8	0.931	1.019	0.939	0.939	0.975	0.962	0.962	1.011	**0.859**	**0.876**	**0.912**
		10	0.998	1.058	1.015	1.015	1.368	1.243	1.243	**0.996**	**0.862**	**0.938**	**0.994**
		12	1.081	**1.057**	**1.077**	**1.077**	3.208	2.754	2.754	1.085	**0.889**	**1.027**	**1.079**
	Traffic	6	0.226	0.278	0.246	0.246	0.570	0.486	0.486	0.251	0.239	0.242	**0.196**
		8	0.214	0.225	0.223	0.223	**0.200**	**0.204**	**0.204**	0.224	0.218	0.221	**0.207**
		10	0.216	0.229	0.227	0.227	0.275	0.241	0.241	0.229	0.226	0.221	**0.209**
		12	0.274	0.293	0.283	0.283	0.679	0.534	0.534	0.293	**0.271**	0.286	**0.264**

Table 28: Multimodal fusion strategies with **iTransformer** (+ **BERT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
iTransformer	Agriculture	6	0.059	0.060	0.062	**0.057**	0.060	**0.058**	1.036	0.060	0.060	0.060	**0.059**
		8	0.077	0.079	0.082	**0.072**	**0.077**	0.080	1.057	0.081	0.079	0.081	**0.076**
		10	0.096	0.104	0.103	**0.090**	0.101	0.102	0.301	0.103	0.101	0.103	0.099
		12	0.128	0.131	0.134	**0.117**	0.131	0.133	0.303	**0.127**	0.132	0.129	**0.125**
	Climate	6	1.096	1.185	1.174	1.131	1.122	1.212	1.326	1.123	1.168	1.151	1.121
		8	1.178	1.207	1.232	1.202	**1.169**	1.215	1.187	1.231	1.258	1.203	1.236
		10	1.186	1.211	1.223	1.188	**1.182**	1.249	**1.050**	1.225	1.223	1.231	1.212
		12	1.176	**1.175**	**1.155**	1.179	**1.155**	1.180	**1.037**	**1.149**	1.211	1.177	1.187
	Economy	6	0.015	0.015	**0.015**	0.018	**0.015**	0.015	15.914	**0.015**	0.016	0.015	**0.014**
		8	0.015	**0.015**	**0.015**	0.019	**0.014**	0.016	10.060	0.015	0.016	0.016	0.016
		10	0.015	0.016	**0.015**	0.016	**0.015**	0.016	0.884	**0.015**	0.016	0.016	**0.015**
		12	0.016	**0.016**	**0.016**	0.019	**0.015**	**0.016**	1.016	**0.016**	**0.016**	**0.016**	**0.016**
	Energy	12	0.111	**0.104**	**0.103**	0.115	**0.102**	**0.110**	0.224	**0.103**	**0.108**	**0.108**	0.112
		24	0.228	**0.217**	**0.226**	**0.207**	**0.194**	**0.217**	0.732	**0.225**	**0.227**	**0.203**	**0.222**
		36	0.302	**0.282**	0.311	0.306	**0.257**	0.305	1.241	0.312	**0.295**	**0.301**	**0.295**
		48	0.408	**0.398**	**0.369**	**0.400**	**0.401**	**0.384**	0.663	**0.394**	**0.405**	**0.393**	**0.393**
	Environment	48	0.411	0.427	**0.411**	0.422	0.412	0.430	0.510	0.411	**0.411**	**0.405**	0.416
		96	0.418	0.426	0.426	0.445	0.444	0.431	0.647	0.433	0.425	0.421	0.438
		192	0.435	**0.434**	**0.420**	0.460	0.437	0.451	0.570	**0.433**	0.443	**0.432**	0.439
		336	0.418	0.420	0.422	0.442	**0.417**	0.422	**0.414**	0.425	0.422	0.420	0.428
	Public Health	12	1.023	**0.969**	1.036	**0.942**	1.058	**0.976**	**1.007**	1.039	**0.972**	**0.953**	**0.975**
		24	1.438	1.465	1.452	**1.209**	1.446	**1.435**	1.550	1.449	1.462	1.440	1.460
		36	1.637	1.667	**1.619**	**1.290**	1.677	**1.617**	1.877	**1.617**	**1.631**	**1.626**	**1.628**
		48	1.738	1.747	**1.735**	**1.468**	1.795	**1.721**	**1.733**	**1.733**	1.749	1.748	1.752
	Security	6	104.9	**104.2**	**102.5**	**102.1**	**103.0**	**103.6**	133.0	**102.7**	**104.7**	**102.9**	**104.0**
		8	108.7	**106.8**	**106.3**	114.0	**106.4**	**105.7**	134.6	**107.0**	**106.1**	**106.3**	108.9
		10	111.4	**111.4**	**107.9**	**109.5**	**109.3**	**108.4**	120.8	**108.1**	**109.5**	**108.3**	**110.6**
		12	114.0	**111.4**	**109.8**	119.7	**110.9**	**110.7**	118.2	**111.1**	**111.9**	**111.1**	**111.8**
	Social Good	6	0.825	0.826	**0.823**	**0.782**	0.841	**0.820**	4.269	**0.823**	**0.817**	**0.823**	**0.804**
		8	0.961	**0.958**	0.966	**0.895**	**0.923**	**0.948**	2.482	0.968	**0.941**	**0.947**	**0.921**
		10	1.061	1.065	**1.058**	**0.986**	1.077	**1.042**	1.128	**1.057**	**1.051**	**1.039**	**1.047**
		12	1.144	1.152	1.166	**1.103**	**1.127**	1.166	**1.124**	**1.046**	**1.134**	**1.139**	**1.048**
	Traffic	6	0.179	0.191	**0.170**	0.190	0.186	**0.163**	0.574	**0.177**	**0.173**	**0.163**	**0.173**
		8	0.185	**0.182**	0.192	0.198	0.195	**0.181**	1.358	0.186	**0.180**	**0.175**	0.189
		10	0.195	0.196	**0.183**	0.203	0.198	**0.191**	0.252	**0.185**	**0.181**	**0.185**	**0.186**
		12	0.249	**0.238**	**0.240**	0.255	0.251	0.254	0.251	**0.242**	**0.236**	**0.241**	**0.235**

Table 29: Multimodal fusion strategies with **DLinear** (+ **BERT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
DLinear	Agriculture	6	0.114	0.120	0.132	0.132	0.455	0.802	0.392	**0.112**	0.235	0.133	**0.085**
		8	0.324	**0.173**	**0.175**	**0.183**	1.168	1.372	1.182	**0.206**	**0.232**	**0.221**	**0.099**
		10	0.163	0.198	0.203	0.209	0.532	0.445	0.436	0.197	0.221	0.216	**0.127**
		12	0.217	0.241	0.243	0.242	0.446	0.364	0.426	**0.162**	0.348	**0.180**	**0.183**
	Climate	6	1.198	1.292	1.255	1.226	1.312	1.241	1.226	1.312	**1.080**	1.285	**1.090**
		8	1.364	**1.329**	**1.288**	**1.264**	**1.240**	**1.172**	**1.160**	**1.318**	**1.084**	1.368	**1.090**
		10	1.166	1.326	1.336	1.306	1.193	**1.125**	**1.122**	1.281	**1.109**	1.314	**1.116**
		12	1.174	1.350	1.356	1.337	**1.164**	**1.131**	**1.129**	1.336	**1.087**	1.281	**1.098**
	Economy	6	0.090	0.092	0.097	0.098	18.050	15.149	13.841	0.107	0.431	0.109	**0.024**
		8	0.233	**0.133**	**0.141**	**0.143**	11.973	10.792	11.650	**0.131**	**0.184**	**0.154**	**0.025**
		10	0.086	0.120	0.130	0.130	2.488	2.169	2.265	0.139	0.148	0.145	**0.051**
		12	0.109	0.119	0.130	0.131	1.543	1.613	1.759	**0.065**	0.230	**0.092**	**0.060**
	Energy	12	0.115	0.211	0.165	0.150	0.228	0.191	0.166	0.140	0.160	0.138	**0.096**
		24	0.219	0.297	0.277	0.258	0.710	0.284	0.286	0.270	0.290	0.240	**0.201**
		36	0.303	0.357	0.344	0.328	1.065	0.349	0.345	0.338	0.355	0.344	**0.284**
		48	0.415	0.440	0.471	0.429	0.679	0.705	0.673	0.443	0.445	0.473	**0.391**
	Environment	48	0.490	**0.462**	**0.460**	**0.452**	0.499	**0.472**	**0.462**	0.507	**0.435**	**0.461**	**0.489**
		96	0.568	**0.467**	**0.473**	**0.459**	**0.537**	**0.491**	**0.476**	**0.565**	**0.474**	**0.466**	0.572
		192	0.583	**0.526**	**0.519**	**0.510**	**0.574**	**0.567**	**0.563**	0.587	**0.582**	**0.518**	0.587
		336	0.538	**0.507**	**0.505**	**0.497**	**0.502**	**0.475**	**0.486**	0.539	**0.508**	**0.495**	0.538
	Public Health	12	1.330	1.457	1.465	1.381	**1.286**	**1.309**	**1.186**	1.664	1.414	1.364	**1.228**
		24	1.578	**1.539**	**1.397**	**1.445**	1.784	1.653	1.605	1.688	1.695	**1.452**	1.589
		36	1.619	1.671	1.688	1.648	2.247	1.750	1.679	1.787	1.843	1.635	1.629
		48	1.691	1.749	1.725	1.724	1.842	1.837	1.809	1.804	1.775	**1.616**	**1.674**
	Security	6	104.4	105.8	105.0	104.5	192.5	176.2	170.7	105.8	110.3	104.6	104.8
		8	109.2	110.0	**108.8**	**108.3**	151.3	149.4	147.6	110.2	**107.0**	**108.6**	**109.0**
		10	110.5	112.5	110.9	110.8	113.0	112.2	112.9	111.0	**106.1**	110.8	**109.7**
		12	112.0	114.5	114.4	113.3	113.4	112.8	113.4	113.3	**111.2**	113.2	**111.7**
	Social Good	6	0.817	0.941	0.949	0.918	3.033	2.072	1.869	0.922	0.931	0.878	**0.779**
		8	0.885	1.055	1.029	1.004	2.522	2.304	2.139	0.958	0.960	0.966	**0.870**
		10	1.026	1.158	1.142	1.108	1.103	**0.962**	**0.951**	1.180	**0.987**	1.131	**0.966**
		12	1.010	1.232	1.155	1.240	1.054	1.011	**1.004**	1.089	1.045	1.128	**1.003**
	Traffic	6	0.254	0.302	0.328	0.309	0.673	0.677	0.618	0.313	0.371	0.313	**0.227**
		8	0.322	0.337	0.359	0.341	1.617	2.183	1.528	**0.269**	0.332	0.359	**0.224**
		10	0.243	0.334	0.354	0.341	0.511	0.297	0.358	0.294	0.314	0.357	**0.219**
		12	0.287	0.363	0.390	0.379	0.562	0.375	0.525	0.327	0.316	0.332	**0.261**

Table 30: Multimodal fusion strategies with **PatchTST** (+ **BERT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
PatchTST	Agriculture	6	0.059	0.060	0.062	**0.057**	0.060	0.061	0.639	0.062	**0.059**	0.060	**0.059**
		8	0.078	0.079	0.081	**0.076**	0.079	0.080	0.814	0.081	0.079	0.079	**0.077**
		10	0.100	**0.099**	0.101	**0.097**	**0.099**	0.102	0.342	0.101	0.102	0.101	0.100
		12	0.129	**0.129**	**0.129**	**0.120**	**0.129**	0.129	0.394	**0.128**	**0.129**	0.130	**0.129**
	Climate	6	1.257	**1.234**	**1.240**	**1.237**	**1.234**	1.259	1.352	**1.240**	1.263	**1.224**	**1.225**
		8	1.265	**1.255**	**1.226**	**1.263**	**1.255**	**1.250**	**1.135**	**1.226**	**1.257**	**1.230**	**1.253**
		10	1.274	1.276	**1.261**	1.281	1.276	**1.272**	**1.093**	**1.261**	**1.271**	**1.250**	1.276
		12	1.239	1.248	1.246	1.260	1.248	1.257	**1.095**	1.246	1.269	1.242	1.253
	Economy	6	0.016	0.016	**0.016**	0.017	0.016	0.018	16.300	0.017	0.018	0.017	0.016
		8	0.017	**0.017**	0.018	0.019	**0.017**	**0.017**	9.731	0.018	0.018	0.018	0.017
		10	0.017	0.017	**0.017**	0.019	0.017	0.017	1.014	**0.017**	0.018	0.017	0.017
		12	0.017	0.018	**0.017**	0.022	0.018	0.018	1.012	0.018	0.018	0.018	0.018
	Energy	12	0.105	**0.102**	0.111	0.112	**0.102**	0.107	0.226	0.111	0.106	0.111	0.113
		24	0.226	0.227	**0.213**	**0.213**	0.227	**0.216**	0.639	**0.213**	**0.208**	**0.213**	**0.215**
		36	0.310	**0.302**	**0.310**	**0.290**	**0.302**	**0.290**	1.382	**0.310**	**0.309**	**0.301**	**0.306**
		48	0.414	0.430	0.417	**0.392**	0.430	0.419	0.644	0.416	**0.405**	0.416	0.418
	Environment	48	0.459	0.461	**0.458**	**0.455**	0.461	**0.451**	0.514	**0.458**	**0.452**	0.462	**0.447**
		96	0.504	0.511	**0.450**	**0.476**	0.511	**0.486**	0.690	**0.465**	**0.439**	**0.457**	**0.449**
		192	0.548	**0.536**	**0.443**	**0.519**	**0.536**	**0.494**	0.657	**0.445**	**0.456**	**0.452**	**0.438**
		336	0.497	0.500	**0.437**	0.519	0.500	**0.452**	**0.471**	**0.457**	**0.458**	**0.447**	**0.433**
	Public Health	12	0.913	**0.891**	0.926	**0.774**	**0.891**	0.948	1.011	0.932	**0.869**	**0.912**	**0.907**
		24	1.299	1.316	1.389	**1.163**	1.316	1.381	1.689	1.331	1.334	1.326	1.301
		36	1.623	**1.620**	**1.607**	**1.366**	**1.620**	**1.618**	**1.480**	**1.607**	**1.605**	**1.613**	**1.596**
		48	1.724	1.727	1.731	**1.474**	1.727	1.724	**1.709**	1.731	1.727	**1.724**	1.754
	Security	6	104.5	**104.3**	**102.5**	**104.2**	**104.3**	**103.3**	140.4	**102.4**	105.0	**102.9**	104.5
		8	110.1	**109.6**	**105.3**	**107.9**	**109.6**	**106.3**	138.0	**105.1**	**108.1**	**107.3**	**107.4**
		10	112.5	**109.9**	**108.9**	**109.7**	**109.9**	**108.3**	118.2	**107.6**	**110.2**	**109.3**	**110.7**
		12	110.8	111.4	**110.2**	**110.3**	111.4	112.2	118.4	**110.7**	**110.7**	112.7	113.7
	Social Good	6	0.794	0.802	**0.782**	**0.764**	0.802	**0.774**	3.867	**0.782**	**0.786**	**0.793**	**0.772**
		8	0.903	**0.896**	**0.881**	**0.845**	**0.896**	**0.900**	2.718	**0.881**	**0.898**	**0.901**	**0.881**
		10	0.991	1.051	1.046	**0.964**	1.051	1.049	1.102	1.046	1.017	1.032	**0.980**
		12	1.133	**1.113**	**1.063**	**0.988**	**1.113**	**1.070**	**1.091**	**1.062**	**1.057**	**1.088**	**1.047**
	Traffic	6	0.183	**0.181**	**0.182**	0.185	**0.181**	**0.179**	0.363	**0.179**	**0.177**	**0.180**	**0.173**
		8	0.185	**0.178**	0.194	0.197	**0.178**	**0.180**	1.920	0.188	**0.182**	**0.184**	0.192
		10	0.189	**0.188**	**0.183**	0.203	**0.188**	0.194	0.306	**0.186**	**0.185**	**0.180**	**0.183**
		12	0.240	0.244	0.246	0.255	0.244	**0.236**	0.385	0.241	**0.236**	**0.235**	0.257

Table 31: Multimodal fusion strategies with **FiLM** (+ **BERT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	CFA
FiLM	Agriculture	6	0.061	0.083	0.063	0.066	2.706	0.065	1.955	0.063	0.064	0.061	0.063
		8	0.082	0.087	**0.081**	**0.082**	1.423	0.088	0.816	**0.080**	0.083	**0.081**	**0.078**
		10	0.105	21.529	**0.104**	**0.099**	0.149	0.106	0.362	0.107	0.106	**0.102**	**0.103**
		12	0.143	**0.139**	**0.133**	**0.122**	0.973	**0.136**	0.449	**0.133**	**0.137**	**0.137**	**0.132**
	Climate	6	1.305	**1.263**	**1.280**	**1.260**	1.559	**1.264**	**1.299**	**1.219**	**1.293**	**1.237**	**1.254**
		8	1.282	**1.273**	**1.277**	**1.269**	**1.034**	1.317	**1.155**	1.310	**1.269**	**1.270**	**1.264**
		10	1.278	10.976	1.305	1.280	14.518	1.297	**1.106**	1.284	1.287	**1.272**	**1.273**
		12	1.280	21.682	1.280	1.288	9.379	1.285	**1.112**	1.308	1.281	1.318	**1.264**
	Economy	6	0.017	0.037	0.027	0.033	21.352	0.021	18.802	0.019	0.018	0.018	0.017
		8	0.018	0.047	0.021	0.021	11.280	0.023	13.157	**0.018**	**0.017**	0.018	0.018
		10	0.019	0.040	0.019	**0.018**	0.553	0.022	2.364	**0.018**	**0.018**	**0.018**	**0.018**
		12	0.018	36.534	0.020	0.043	1.685	0.021	2.238	**0.018**	0.018	**0.018**	**0.018**
	Energy	12	0.119	9874.3	0.120	0.132	0.321	0.148	0.199	**0.105**	**0.107**	**0.109**	**0.102**
		24	0.229	0.358	0.256	0.266	0.725	0.252	0.725	**0.215**	**0.219**	0.233	**0.206**
		36	0.302	34795.4	0.320	0.335	1.481	0.323	1.351	**0.300**	0.315	0.309	**0.300**
		48	0.435	0.486	0.443	0.443	0.699	0.506	0.673	**0.419**	**0.430**	0.448	**0.429**
	Environment	48	0.488	218219.0	**0.482**	**0.486**	0.499	**0.488**	0.500	0.491	**0.477**	**0.466**	0.490
		96	0.546	35537.8	**0.512**	**0.494**	0.579	**0.483**	0.604	0.546	**0.531**	**0.494**	**0.540**
		192	0.574	3251248128.0	**0.542**	**0.546**	0.604	**0.498**	0.671	0.575	**0.549**	**0.514**	**0.570**
		336	0.529	2551701760.0	**0.478**	**0.522**	58696568.0	**0.499**	**0.486**	**0.527**	**0.481**	**0.500**	**0.527**
	Public Health	12	1.155	3605.6	1.195	1.184	2.073	1.481	1.249	**1.121**	**1.138**	**1.129**	**1.106**
		24	1.492	**1.417**	1.496	**1.371**	3.481	1.646	**1.450**	**1.450**	**1.482**	**1.425**	**1.432**
		36	1.635	1.686	1.658	1.853	2.602	1.668	2.357	1.719	1.692	1.642	1.685
		48	1.722	2.066	1.775	2.052	2.202	1.790	1.850	1.728	1.806	1.776	1.739
	Security	6	124.2	**106.8**	**102.1**	**100.9**	210.4	**103.4**	189.5	**102.8**	**101.6**	**102.0**	**107.1**
		8	113.8	116.8	**106.0**	116.4	148.3	**105.5**	164.3	**110.8**	**106.3**	**106.2**	**105.1**
		10	117.0	136.7	**109.0**	133.4	**95.991**	**107.9**	**111.8**	**109.4**	**108.2**	**108.8**	**114.0**
		12	119.0	128.9	**109.8**	**108.2**	**98.285**	**111.2**	**113.1**	**112.2**	**113.6**	**111.6**	**113.8**
	Social Good	6	0.900	193.9	**0.854**	**0.827**	4.318	**0.848**	4.221	**0.819**	**0.810**	**0.815**	**0.818**
		8	0.994	1.363	1.005	1.027	2.158	1.055	2.760	1.002	**0.964**	**0.944**	**0.967**
		10	1.119	397.3	**1.040**	1.202	423.6	**1.106**	**1.096**	**1.014**	**1.112**	**1.046**	1.123
		12	1.216	1045.6	**1.074**	**1.071**	320.6	**1.182**	**1.081**	1.218	**1.191**	**1.154**	**1.165**
	Traffic	6	0.229	0.298	0.234	0.252	1.395	0.235	0.606	0.268	**0.229**	0.239	0.236
		8	0.223	**0.218**	**0.220**	**0.221**	2.319	0.229	1.438	0.230	0.226	**0.220**	0.233
		10	0.216	0.227	0.217	**0.215**	0.300	0.218	0.423	0.240	0.220	0.217	**0.215**
		12	0.253	1.605	**0.252**	0.270	**0.242**	0.268	0.326	0.285	0.258	0.274	**0.251**

Table 32: Multimodal fusion strategies with **TiDE** (+ **BERT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	CFA
TiDE	Agriculture	6	0.073	**0.068**	0.082	**0.068**	1.720	**0.065**	1.699	**0.063**	**0.063**	**0.062**	**0.060**
		8	0.088	0.091	0.092	0.092	1.005	0.093	0.826	**0.082**	**0.082**	**0.080**	**0.082**
		10	0.112	17.163	**0.110**	0.112	19.212	0.120	0.419	**0.103**	**0.104**	**0.104**	**0.103**
		12	0.160	20.607	**0.144**	**0.124**	29.733	**0.150**	0.353	**0.135**	**0.134**	**0.134**	**0.135**
	Climate	6	1.515	1.601	1.606	1.600	**1.496**	**1.418**	**1.379**	**1.252**	**1.244**	**1.239**	**1.258**
		8	1.486	1.567	**1.481**	**1.458**	**1.081**	1.532	**1.184**	**1.264**	**1.274**	**1.258**	**1.267**
		10	1.408	14.350	1.467	1.486	5.718	1.561	**1.197**	**1.274**	**1.272**	**1.259**	**1.259**
		12	1.468	10.739	**1.395**	1.480	3.521	1.508	**1.164**	**1.255**	**1.278**	**1.264**	**1.271**
	Economy	6	0.033	0.052	0.039	0.053	19.510	0.044	19.047	**0.017**	**0.017**	**0.017**	**0.017**
		8	0.043	**0.042**	**0.035**	**0.041**	12.450	**0.031**	12.775	**0.017**	**0.018**	**0.017**	**0.018**
		10	0.030	24.102	0.031	0.039	47.478	0.040	1.857	**0.018**	**0.017**	**0.017**	**0.017**
		12	0.033	27.894	**0.031**	0.037	57.638	0.038	1.946	**0.018**	**0.018**	**0.019**	**0.017**
	Energy	12	0.135	8167.2	0.139	0.135	2692.9	**0.134**	0.214	**0.115**	**0.115**	**0.108**	**0.112**
		24	0.241	0.389	0.244	0.262	0.779	0.243	0.784	**0.212**	**0.210**	**0.217**	**0.220**
		36	0.330	26003.6	0.333	**0.328**	8011.0	0.332	1.382	**0.294**	**0.307**	**0.305**	**0.300**
		48	0.443	0.467	0.443	**0.439**	0.684	**0.442**	0.692	**0.403**	**0.414**	**0.407**	**0.408**
	Environment	48	0.484	0.808	0.485	**0.475**	**0.472**	0.485	**0.483**	0.485	**0.483**	0.485	**0.484**
		96	0.541	**0.512**	0.542	**0.513**	0.570	**0.539**	0.630	0.541	**0.539**	**0.539**	**0.540**
		192	0.577	8866.8	0.578	**0.561**	5217.4	**0.577**	0.612	**0.577**	**0.577**	**0.577**	**0.576**
		336	0.533	7686.4	0.534	**0.510**	977.9	0.533	**0.494**	0.534	0.533	0.533	0.534
	Public Health	12	1.299	1837.7	1.320	1.328	1131.5	1.329	**1.244**	**1.076**	**1.128**	**1.113**	**1.106**
		24	1.513	2.180	**1.499**	1.646	1.673	1.567	1.685	**1.432**	**1.434**	**1.448**	**1.425**
		36	1.676	11842.9	**1.668**	1.755	5477.2	**1.669**	2.308	**1.605**	**1.619**	**1.617**	**1.602**
		48	1.787	1.977	**1.756**	1.844	1.845	1.788	**1.773**	**1.724**	**1.723**	**1.726**	**1.721**
	Security	6	146.1	**125.0**	**134.9**	**125.0**	202.6	**122.2**	192.6	**105.2**	**107.2**	**107.6**	**107.5**
		8	129.7	138.8	132.5	138.7	154.2	**128.9**	155.8	**108.3**	**108.9**	**112.4**	**109.4**
		10	132.3	162.6	135.2	134.7	**101.0**	135.4	**116.3**	**112.7**	**110.6**	**114.6**	**111.9**
		12	145.2	149.2	**139.2**	**139.4**	**102.7**	**142.4**	**119.8**	**112.7**	**112.3**	**112.3**	**111.7**
	Social Good	6	1.012	**0.974**	1.036	**0.961**	3.988	**0.970**	3.950	**0.835**	**0.836**	**0.823**	**0.843**
		8	1.062	1.129	**1.013**	1.129	2.673	**1.044**	2.480	**0.950**	**0.940**	**0.950**	**0.947**
		10	1.250	571.2	**1.097**	**1.185**	269.0	**1.243**	**1.011**	**1.068**	**1.070**	**1.109**	**1.068**
		12	1.415	737.3	**1.186**	**1.298**	231.7	**1.205**	**1.059**	**1.162**	**1.252**	**1.183**	**1.147**
	Traffic	6	0.304	0.326	**0.285**	0.326	0.439	**0.301**	0.438	**0.236**	**0.235**	**0.236**	**0.233**
		8	0.309	0.312	**0.277**	0.310	0.469	**0.272**	0.424	**0.233**	**0.230**	**0.234**	**0.224**
		10	0.249	31.614	**0.245**	0.328	9.288	0.302	0.623	**0.224**	**0.231**	**0.225**	**0.229**
		12	0.319	39.803	**0.308**	0.336	13.868	0.334	0.404	**0.288**	**0.290**	**0.284**	**0.289**

Table 33: Multimodal fusion strategies with **FEDformer** (+ **BERT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
FEDformer	Agriculture	6	0.062	0.063	0.062	**0.057**	**0.061**	**0.062**	0.604	0.064	**0.062**	**0.055**	**0.059**
		8	0.071	0.076	0.074	**0.071**	0.083	0.073	0.726	0.075	0.078	**0.069**	**0.069**
		10	0.092	0.103	**0.090**	0.094	0.104	0.096	0.362	0.095	0.093	0.092	0.093
		12	0.115	0.118	0.116	0.123	0.131	0.122	0.316	0.116	0.122	0.122	0.117
	Climate	6	1.116	**1.061**	**1.098**	1.182	**1.071**	**1.086**	1.261	**1.098**	**1.095**	**1.077**	**1.060**
		8	1.082	1.091	**1.060**	1.091	**1.030**	**1.063**	**1.051**	**1.055**	1.093	**1.075**	1.101
		10	1.105	**1.102**	1.109	1.108	**1.053**	1.115	**0.896**	1.111	**1.095**	**1.098**	**1.066**
		12	1.084	1.116	1.100	1.092	1.118	**1.054**	**0.931**	1.100	1.120	1.112	1.093
	Economy	6	0.039	0.047	0.049	**0.036**	0.041	0.045	10.229	0.049	0.046	**0.029**	0.048
		8	0.047	0.053	0.053	0.050	**0.029**	**0.036**	7.842	0.052	**0.036**	0.053	**0.041**
		10	0.040	0.051	0.048	0.045	0.051	**0.035**	0.900	0.048	0.041	**0.036**	0.044
		12	0.046	**0.045**	**0.041**	0.056	0.046	**0.032**	1.095	**0.040**	**0.037**	0.047	**0.044**
	Energy	12	0.098	0.111	**0.094**	**0.096**	0.113	**0.093**	0.129	**0.094**	**0.097**	**0.091**	**0.092**
		24	0.183	0.184	0.184	**0.175**	0.184	**0.179**	0.790	0.184	**0.176**	**0.178**	**0.179**
		36	0.254	0.332	0.268	**0.251**	0.304	0.257	0.792	0.261	**0.253**	**0.253**	0.256
		48	0.375	0.403	**0.370**	**0.367**	0.474	**0.359**	0.776	**0.370**	**0.366**	**0.358**	0.386
	Environment	48	0.443	0.502	0.478	0.486	0.473	0.467	0.503	0.479	0.482	0.458	0.471
		96	0.487	0.511	**0.486**	0.527	0.513	0.518	**0.445**	**0.480**	**0.480**	0.491	**0.457**
		192	0.508	0.508	**0.505**	**0.505**	0.509	**0.499**	**0.469**	**0.508**	**0.495**	0.513	**0.503**
		336	0.449	0.485	0.458	0.486	0.463	0.484	0.454	0.460	0.466	0.470	**0.449**
	Public Health	12	1.050	1.051	1.059	1.056	1.154	1.057	1.058	1.051	1.054	1.098	1.052
		24	1.488	**1.370**	**1.353**	**1.370**	1.531	**1.422**	1.580	**1.348**	**1.407**	**1.374**	**1.350**
		36	1.422	1.552	1.579	1.554	1.504	1.493	1.924	1.544	1.487	1.537	1.502
		48	1.621	**1.568**	**1.601**	1.625	1.738	**1.501**	**1.504**	**1.541**	1.622	**1.610**	**1.502**
	Security	6	105.9	110.1	**103.6**	**102.9**	106.2	**105.7**	162.7	**105.9**	115.0	**104.6**	107.4
		8	109.1	**107.8**	109.8	**108.7**	110.3	109.6	142.9	109.4	110.1	**107.4**	109.6
		10	113.8	**112.9**	**111.6**	**111.4**	**112.3**	114.9	114.0	**111.6**	**113.0**	**110.0**	**113.3**
		12	117.2	117.5	**115.0**	**114.8**	**114.2**	**112.9**	**115.8**	**111.8**	**115.2**	**115.5**	**114.4**
	Social Good	6	0.879	**0.853**	**0.808**	**0.873**	**0.860**	**0.819**	1.825	**0.808**	**0.771**	**0.802**	**0.836**
		8	0.885	**0.873**	0.897	**0.848**	0.905	**0.852**	2.121	0.896	**0.855**	**0.848**	**0.848**
		10	0.914	0.918	**0.892**	0.920	0.982	0.940	0.984	**0.892**	**0.896**	**0.911**	**0.908**
		12	1.015	**0.987**	**0.983**	**0.954**	1.114	**1.010**	1.108	**0.981**	**0.987**	**1.001**	**0.971**
	Traffic	6	0.152	0.163	0.153	0.160	**0.144**	**0.149**	0.351	0.154	0.164	**0.150**	0.153
		8	0.153	0.160	0.156	0.169	**0.144**	0.158	0.227	0.156	0.154	0.156	0.159
		10	0.166	0.175	0.167	0.168	**0.147**	**0.161**	0.344	0.168	**0.163**	**0.161**	**0.161**
		12	0.228	0.233	0.232	0.240	**0.217**	**0.213**	0.376	0.232	0.233	**0.221**	**0.228**

Table 34: Multimodal fusion strategies with **Autoformer** (+ **BERT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Autoformer	Agriculture	6	0.070	0.072	**0.066**	0.075	**0.066**	**0.066**	1.226	**0.069**	**0.069**	**0.062**	**0.068**
		8	0.090	**0.086**	**0.080**	**0.086**	0.091	**0.078**	0.483	0.094	0.097	**0.077**	0.093
		10	0.110	0.117	**0.106**	**0.107**	0.115	0.112	0.348	0.111	**0.102**	0.113	**0.094**
		12	0.128	0.144	0.135	0.139	0.141	0.134	0.446	0.131	0.139	**0.126**	0.129
	Climate	6	1.240	1.292	1.243	**1.222**	**1.182**	**1.206**	1.319	**1.228**	**1.239**	**1.206**	**1.204**
		8	1.200	1.224	1.252	1.203	1.293	**1.176**	**1.103**	1.296	**1.178**	1.221	**1.106**
		10	1.247	1.275	**1.228**	**1.211**	**1.239**	**1.190**	**1.035**	1.256	**1.206**	**1.168**	**1.197**
		12	1.177	1.181	1.216	1.247	1.207	1.192	**0.991**	1.219	1.206	1.194	**1.133**
	Economy	6	0.051	0.077	0.068	0.067	0.058	0.058	11.732	0.069	0.074	0.067	**0.050**
		8	0.058	0.069	**0.058**	**0.058**	0.065	0.065	9.985	**0.058**	0.066	0.061	0.074
		10	0.060	0.066	**0.057**	**0.049**	0.072	**0.049**	1.110	**0.057**	0.067	**0.055**	**0.055**
		12	0.061	0.074	**0.044**	**0.059**	0.074	**0.056**	1.045	**0.056**	**0.052**	**0.051**	**0.045**
	Energy	12	0.165	0.208	**0.158**	**0.158**	0.171	**0.145**	0.339	**0.140**	**0.144**	0.166	0.171
		24	0.292	0.300	0.314	0.296	0.329	0.296	0.710	0.312	0.305	0.329	**0.291**
		36	0.352	0.383	0.378	0.399	0.403	0.387	1.380	0.366	0.385	0.370	0.374
		48	0.485	**0.468**	**0.479**	**0.452**	0.500	**0.476**	0.702	**0.446**	0.491	**0.456**	**0.464**
	Environment	48	0.550	**0.507**	**0.502**	0.558	**0.532**	**0.515**	**0.481**	**0.498**	**0.541**	**0.492**	**0.485**
		96	0.520	0.567	0.524	**0.491**	0.559	**0.511**	0.536	**0.518**	0.544	**0.508**	**0.496**
		192	0.589	**0.550**	**0.547**	**0.560**	0.614	**0.531**	**0.505**	**0.541**	**0.555**	**0.553**	**0.505**
		336	0.565	**0.525**	**0.523**	**0.536**	**0.548**	**0.508**	**0.483**	**0.504**	**0.549**	**0.535**	**0.502**
	Public Health	12	1.668	**1.632**	**1.513**	**1.596**	**1.425**	**1.655**	**1.449**	**1.626**	**1.522**	**1.609**	**1.567**
		24	1.940	2.128	**1.847**	1.941	**1.773**	1.950	**1.639**	**1.845**	1.958	1.989	**1.860**
		36	1.931	1.983	**1.878**	**1.851**	2.105	1.961	2.163	**1.916**	2.008	2.005	**1.883**
		48	1.767	2.137	1.814	1.883	2.048	1.905	1.801	2.026	1.887	1.985	1.926
	Security	6	106.1	107.9	111.8	107.9	**105.7**	111.6	151.7	113.4	107.9	107.1	108.8
		8	110.7	112.2	**109.0**	112.5	111.0	112.7	140.4	**109.8**	111.4	**110.1**	112.8
		10	115.7	**115.2**	116.1	**115.1**	**111.3**	**110.4**	**115.3**	**114.6**	**112.3**	**111.6**	**113.0**
		12	117.8	**117.2**	**112.1**	**115.4**	**116.0**	118.8	**117.3**	**112.2**	**113.8**	**116.2**	**112.5**
	Social Good	6	0.891	0.900	**0.793**	**0.844**	**0.868**	**0.841**	4.417	**0.839**	**0.884**	0.895	**0.814**
		8	0.929	**0.921**	0.952	0.961	1.064	1.020	2.750	0.979	0.931	0.938	0.967
		10	1.052	**1.041**	1.088	**0.996**	1.120	**1.003**	1.125	1.060	1.059	**1.005**	**1.036**
		12	1.194	**1.117**	**1.062**	**1.047**	**1.175**	**1.077**	**1.095**	**1.104**	1.224	**1.115**	**1.151**
	Traffic	6	0.172	0.207	**0.168**	0.183	0.191	**0.166**	0.386	0.182	0.178	0.173	0.186
		8	0.207	**0.197**	0.207	**0.193**	0.222	**0.167**	0.899	0.216	**0.189**	**0.195**	**0.198**
		10	0.191	**0.189**	0.202	0.205	0.197	**0.188**	0.393	0.203	0.193	0.201	0.201
		12	0.239	0.280	**0.236**	0.249	0.265	**0.232**	0.353	**0.234**	**0.234**	**0.226**	**0.232**

Table 35: Multimodal fusion strategies with **Crossformer** (+ **BERT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Crossformer	Agriculture	6	0.088	0.136	0.218	0.152	0.153	0.125	0.221	0.114	0.179	0.130	0.176
		8	0.196	0.219	0.223	0.206	0.891	**0.176**	0.347	0.248	**0.103**	0.207	0.224
		10	0.248	0.318	**0.218**	0.385	0.266	0.413	0.412	0.300	0.272	0.276	0.265
		12	0.311	0.366	**0.253**	0.411	0.602	0.410	0.484	**0.242**	0.315	0.364	0.323
	Climate	6	1.039	**1.018**	1.087	1.091	1.056	1.061	1.055	1.080	1.063	1.061	1.089
		8	1.080	**1.070**	**1.031**	1.097	1.113	1.083	1.084	1.111	1.092	1.092	1.120
		10	1.088	1.117	1.092	1.101	**1.083**	**1.075**	1.110	1.107	**1.082**	1.098	**1.087**
		12	1.090	1.118	**1.086**	1.134	1.134	**1.080**	**1.087**	1.091	1.091	**1.088**	1.117
	Economy	6	0.468	**0.444**	**0.260**	**0.409**	**0.360**	0.671	0.472	0.479	**0.120**	**0.089**	**0.149**
		8	0.123	0.612	0.299	0.641	6.351	0.452	0.911	0.554	**0.096**	0.403	0.488
		10	0.122	0.683	0.378	0.463	0.535	1.044	0.796	0.819	0.356	0.654	0.270
		12	0.323	1.084	0.727	0.773	0.641	0.966	0.615	0.339	0.535	0.851	0.379
	Energy	12	0.145	**0.130**	**0.133**	0.148	0.146	**0.138**	0.152	**0.139**	0.155	**0.130**	**0.143**
		24	0.252	**0.250**	0.258	**0.235**	0.320	**0.226**	0.270	0.256	**0.247**	0.252	**0.247**
		36	0.345	**0.334**	**0.337**	**0.336**	0.346	**0.318**	**0.328**	**0.322**	**0.328**	**0.334**	**0.337**
		48	0.445	0.455	0.446	**0.441**	**0.413**	**0.440**	**0.382**	**0.425**	0.454	0.450	**0.435**
	Environment	48	0.492	**0.444**	**0.457**	0.498	**0.444**	**0.445**	**0.442**	**0.450**	**0.456**	**0.462**	**0.439**
		96	0.589	**0.461**	**0.494**	**0.520**	**0.472**	**0.473**	**0.519**	**0.473**	**0.486**	**0.493**	**0.475**
		192	0.551	**0.482**	0.573	**0.502**	**0.526**	0.593	0.614	0.590	**0.547**	0.560	**0.497**
		336	0.527	0.553	0.555	**0.509**	**0.493**	0.588	0.542	**0.526**	0.547	0.565	**0.503**
	Public Health	12	1.089	1.113	**1.053**	1.125	1.223	**1.048**	1.095	1.100	1.150	1.116	**1.050**
		24	1.305	1.330	1.343	1.311	1.427	1.410	1.408	1.401	1.324	1.305	1.330
		36	1.321	**1.280**	1.397	1.411	1.381	1.365	1.382	1.369	1.367	1.370	**1.321**
		48	1.440	1.511	1.451	1.490	1.448	1.452	1.555	1.521	1.486	1.472	1.525
	Security	6	118.2	121.5	119.0	120.6	120.9	122.2	125.1	119.9	124.1	118.9	**117.3**
		8	121.3	124.4	125.2	124.2	130.9	**120.7**	126.1	123.7	123.8	123.5	**120.5**
		10	125.3	126.1	**125.1**	125.9	**123.9**	**124.5**	127.6	126.7	126.2	**125.3**	**124.0**
		12	123.3	128.1	126.9	127.6	129.9	129.5	129.3	128.1	127.5	127.6	125.9
	Social Good	6	0.728	0.743	0.749	0.739	0.732	**0.728**	0.747	0.747	0.730	0.765	0.750
		8	0.816	0.834	**0.800**	**0.813**	1.874	**0.805**	**0.812**	**0.810**	0.819	0.832	**0.816**
		10	0.872	0.914	0.915	0.887	**0.859**	0.881	0.872	**0.863**	**0.865**	0.883	0.880
		12	0.936	0.953	**0.897**	0.947	**0.916**	**0.893**	0.949	**0.909**	**0.913**	**0.908**	**0.933**
	Traffic	6	0.215	**0.210**	0.219	**0.213**	0.229	**0.214**	**0.211**	**0.213**	0.220	**0.210**	0.220
		8	0.208	0.215	0.209	0.210	0.353	0.221	**0.203**	0.216	0.213	0.236	0.232
		10	0.211	0.226	0.225	0.226	0.225	0.225	0.223	0.223	0.221	0.216	0.222
		12	0.254	**0.250**	**0.244**	**0.245**	0.301	**0.242**	**0.250**	**0.250**	**0.242**	**0.250**	**0.249**

Table 36: Multimodal fusion strategies with **Reformer** (+ **BERT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Reformer	Agriculture	6	0.202	0.231	**0.147**	**0.152**	0.255	**0.174**	0.317	**0.150**	0.231	0.220	**0.163**
		8	0.221	0.411	0.302	0.239	0.242	0.369	0.416	0.304	**0.187**	**0.191**	0.233
		10	0.319	0.525	0.452	0.416	0.523	**0.314**	0.714	0.328	**0.251**	0.457	**0.246**
		12	0.533	**0.514**	**0.392**	**0.496**	0.615	0.721	**0.377**	**0.316**	**0.277**	**0.212**	**0.241**
	Climate	6	1.025	1.102	1.028	1.091	1.064	1.114	1.080	1.038	1.076	**1.011**	1.082
		8	1.066	1.089	1.080	1.069	**1.042**	1.099	1.075	**1.040**	**1.047**	1.085	1.087
		10	1.058	1.107	1.128	1.068	1.092	1.086	**0.892**	1.150	1.078	1.081	1.078
		12	1.076	1.122	**1.068**	**1.036**	1.108	1.103	**1.050**	**0.981**	**1.068**	**1.064**	**1.063**
	Economy	6	0.199	0.390	0.511	0.386	0.607	**0.111**	0.764	0.412	0.511	**0.113**	0.482
		8	0.337	0.460	**0.298**	**0.172**	0.561	**0.305**	1.027	**0.286**	0.679	**0.210**	**0.254**
		10	0.176	0.463	0.689	0.331	0.922	1.135	1.762	0.671	0.549	0.925	0.558
		12	0.144	0.751	1.151	0.489	1.109	1.347	1.129	1.097	1.162	0.802	0.394
	Energy	12	0.207	0.217	0.264	0.247	0.262	0.278	0.243	**0.174**	**0.168**	0.252	0.218
		24	0.423	**0.409**	**0.417**	**0.388**	0.582	**0.408**	**0.364**	**0.325**	**0.311**	**0.397**	**0.356**
		36	0.510	**0.506**	**0.478**	**0.406**	**0.457**	**0.471**	**0.440**	**0.379**	**0.423**	**0.416**	**0.463**
		48	0.575	0.579	**0.565**	**0.539**	0.877	**0.528**	**0.493**	**0.498**	**0.427**	**0.542**	**0.539**
	Environment	48	0.415	0.434	0.416	0.424	0.418	0.422	0.421	0.416	0.415	0.420	**0.397**
		96	0.460	**0.428**	0.479	**0.437**	0.485	**0.399**	0.475	**0.432**	**0.400**	**0.392**	**0.413**
		192	0.430	0.456	0.433	0.443	**0.415**	0.430	0.442	**0.423**	**0.403**	**0.413**	**0.422**
		336	0.451	**0.411**	**0.441**	**0.438**	**0.402**	**0.431**	**0.434**	**0.408**	**0.402**	**0.409**	**0.429**
	Public Health	12	1.200	**1.080**	**1.119**	**1.129**	**1.144**	**1.102**	**1.089**	**1.116**	**1.040**	1.235	**1.131**
		24	1.258	1.297	1.312	1.371	1.375	1.533	1.374	1.301	1.330	1.351	**1.243**
		36	1.321	**1.287**	**1.289**	1.480	1.365	**1.292**	1.332	**1.286**	**1.316**	1.362	**1.286**
		48	1.363	1.482	1.463	**1.346**	1.439	1.529	1.516	1.442	1.399	1.401	1.406
	Security	6	118.3	120.8	123.9	124.2	**118.1**	120.4	122.5	123.9	124.9	124.4	123.8
		8	121.6	**119.8**	121.8	124.0	122.0	125.3	124.9	121.8	123.6	124.1	122.3
		10	126.2	**125.0**	**124.6**	**123.7**	129.0	**124.3**	126.8	**124.6**	**124.9**	**125.6**	**125.4**
		12	128.0	**120.8**	**125.7**	**126.5**	**126.8**	**124.0**	**124.8**	**125.7**	**126.3**	**125.1**	**126.0**
	Social Good	6	0.775	0.843	0.853	0.793	0.836	0.870	0.796	0.880	0.887	**0.773**	0.822
		8	0.864	0.866	0.914	**0.860**	0.921	0.898	**0.850**	0.910	**0.857**	0.889	0.868
		10	0.949	0.962	1.016	**0.912**	1.029	0.971	**0.906**	0.989	**0.943**	**0.909**	0.970
		12	1.006	1.138	**0.976**	**0.953**	**1.002**	**0.988**	**0.980**	**0.974**	**0.958**	**0.961**	**0.985**
	Traffic	6	0.208	0.260	0.226	0.304	0.232	0.289	0.245	0.226	0.287	0.251	0.240
		8	0.224	0.262	**0.224**	**0.218**	0.233	0.296	0.234	**0.224**	0.231	0.237	0.234
		10	0.261	0.265	0.275	**0.246**	**0.246**	0.292	**0.224**	**0.258**	**0.219**	**0.248**	0.263
		12	0.244	0.257	0.264	0.260	0.253	0.283	0.249	0.262	0.267	0.273	0.256

Table 37: Multimodal fusion strategies with **TSMixer** (+ **BERT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
TSMixer	Agriculture	6	0.083	0.135	0.141	0.089	0.105	0.181	0.098	0.139	0.108	0.114	0.108
		8	0.129	0.235	0.298	0.236	0.420	0.276	0.143	0.202	0.230	0.182	**0.122**
		10	0.428	0.934	1.301	0.486	**0.259**	1.325	**0.238**	**0.238**	1.514	0.862	**0.253**
		12	0.660	1.593	1.380	0.978	1.625	**0.588**	**0.594**	**0.590**	1.871	1.654	**0.280**
	Climate	6	1.054	1.067	1.065	1.080	1.085	1.093	1.133	1.059	1.066	1.066	1.070
		8	1.088	1.094	1.098	**1.080**	1.100	**1.086**	1.099	1.107	1.096	**1.080**	1.095
		10	1.105	1.115	1.206	1.146	1.108	1.115	1.136	1.117	1.118	1.124	1.113
		12	1.106	1.193	1.136	1.176	1.156	**1.105**	1.117	1.149	1.154	1.136	1.106
	Economy	6	0.074	0.115	0.142	0.127	0.111	0.099	0.081	0.206	0.140	0.080	**0.050**
		8	0.063	0.327	0.551	0.286	0.980	0.317	0.142	0.321	0.544	0.149	**0.044**
		10	0.109	1.853	2.252	0.929	0.260	2.339	0.172	0.203	1.349	1.855	0.155
		12	0.874	2.740	2.863	3.037	2.808	**0.863**	1.067	**0.504**	2.803	2.758	**0.208**
	Energy	12	0.142	**0.134**	0.146	0.154	0.158	0.144	0.153	**0.129**	0.154	**0.142**	**0.115**
		24	0.286	0.288	**0.276**	0.295	**0.277**	**0.245**	**0.284**	**0.275**	**0.271**	**0.259**	**0.264**
		36	0.360	**0.347**	0.371	0.369	0.380	0.408	0.383	**0.349**	0.409	**0.340**	0.360
		48	0.456	**0.456**	0.483	0.581	**0.405**	0.485	0.458	**0.456**	0.508	0.469	**0.445**
	Environment	48	0.542	**0.440**	**0.451**	**0.459**	**0.445**	**0.449**	**0.482**	**0.526**	**0.443**	**0.437**	**0.502**
		96	0.606	**0.460**	**0.479**	**0.483**	**0.437**	**0.446**	**0.478**	**0.594**	**0.472**	**0.469**	**0.556**
		192	0.660	**0.596**	**0.505**	**0.499**	**0.608**	**0.527**	**0.488**	**0.597**	**0.485**	**0.464**	**0.619**
		336	0.581	0.592	**0.529**	**0.534**	**0.574**	**0.544**	**0.499**	0.582	**0.526**	**0.502**	**0.558**
	Public Health	12	1.150	**0.996**	**1.106**	**1.142**	1.223	**1.105**	**1.145**	**1.115**	1.218	**1.087**	**1.086**
		24	1.393	1.558	1.402	1.410	**1.350**	**1.383**	1.490	**1.326**	1.499	1.445	**1.382**
		36	1.500	1.732	1.654	**1.478**	1.500	1.577	**1.477**	**1.420**	1.614	1.539	**1.466**
		48	1.687	**1.626**	1.736	**1.616**	**1.618**	1.691	**1.601**	**1.518**	**1.671**	**1.648**	**1.625**
	Security	6	128.0	128.4	129.3	129.5	**125.6**	**125.5**	129.2	**124.0**	129.9	128.2	**124.4**
		8	127.4	**124.1**	128.6	**127.2**	**126.8**	**117.2**	132.8	129.4	**127.0**	**125.6**	**126.4**
		10	128.2	131.4	131.4	132.0	128.5	130.8	130.4	133.5	129.4	130.2	128.2
		12	130.7	133.0	133.1	134.1	132.8	**127.4**	**128.9**	133.1	131.7	132.5	131.3
	Social Good	6	0.769	0.843	0.872	0.854	0.781	**0.764**	**0.730**	0.772	0.826	0.811	**0.739**
		8	0.876	0.919	0.974	0.945	**0.792**	0.944	**0.866**	**0.809**	0.946	0.938	**0.855**
		10	0.876	0.961	1.136	0.924	0.883	0.957	0.940	0.910	1.199	1.096	**0.861**
		12	0.942	1.527	1.192	1.036	1.044	0.958	**0.916**	**0.920**	1.186	1.153	**0.839**
	Traffic	6	0.203	0.233	0.232	0.207	0.234	0.223	0.226	0.230	0.298	0.234	**0.190**
		8	0.216	0.258	0.233	0.251	0.268	0.248	0.249	0.279	0.280	0.227	**0.185**
		10	0.229	0.418	0.551	0.331	0.243	0.548	0.230	0.250	0.561	0.286	**0.207**
		12	0.303	0.799	0.632	0.398	0.713	**0.289**	**0.288**	0.324	0.776	0.578	**0.266**

Table 38: Multimodal fusion strategies with **Transformer** (+ **BERT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Transformer	Agriculture	6	0.133	0.133	0.165	0.223	**0.110**	**0.130**	0.275	0.174	**0.130**	0.152	0.146
		8	0.147	0.326	0.152	0.197	0.203	0.201	0.376	0.196	0.162	0.207	0.191
		10	0.177	0.505	0.226	0.266	**0.151**	**0.176**	0.703	0.234	0.177	0.185	**0.158**
		12	0.233	0.373	0.247	0.246	**0.176**	0.319	0.320	0.247	0.244	**0.207**	0.356
	Climate	6	0.985	1.086	0.988	1.043	**0.948**	1.031	1.025	0.988	1.031	1.077	**0.982**
		8	1.058	**1.056**	**0.990**	**1.049**	1.094	1.093	**1.036**	**0.990**	**1.035**	**1.041**	**1.037**
		10	1.068	1.093	**1.052**	**1.042**	1.087	**1.005**	**1.060**	**1.052**	**1.008**	1.073	1.085
		12	1.102	**0.979**	**1.032**	1.117	1.112	**1.084**	**1.063**	**1.032**	**1.050**	**1.064**	**1.026**
	Economy	6	0.267	0.394	**0.067**	0.636	**0.073**	**0.119**	0.718	**0.145**	**0.075**	**0.077**	**0.101**
		8	0.310	0.375	**0.243**	**0.187**	**0.217**	0.383	0.578	0.421	0.471	0.584	**0.245**
		10	0.258	0.678	0.273	0.494	**0.095**	**0.102**	1.304	0.278	0.429	0.312	**0.112**
		12	0.362	0.491	0.492	**0.272**	**0.072**	0.451	0.676	0.542	0.362	**0.330**	**0.086**
	Energy	12	0.122	0.123	**0.104**	0.130	**0.105**	0.143	**0.101**	**0.101**	**0.090**	**0.076**	0.134
		24	0.289	0.349	**0.251**	**0.280**	**0.200**	**0.161**	**0.168**	**0.206**	**0.204**	**0.144**	**0.201**
		36	0.261	0.350	0.312	0.353	0.375	**0.233**	0.319	0.306	0.264	0.283	0.342
		48	0.450	0.480	**0.437**	0.463	**0.439**	**0.389**	0.535	**0.392**	**0.447**	**0.419**	**0.432**
	Environment	48	0.429	0.441	**0.416**	0.432	**0.420**	**0.399**	0.432	**0.412**	**0.406**	**0.414**	**0.419**
		96	0.462	0.470	**0.434**	0.518	**0.438**	**0.445**	**0.444**	**0.407**	**0.441**	**0.438**	**0.425**
		192	0.450	0.503	0.473	0.481	0.462	0.477	0.511	0.463	**0.397**	**0.410**	**0.432**
		336	0.451	0.487	**0.442**	**0.445**	0.464	0.455	0.457	**0.399**	0.454	**0.409**	**0.419**
	Public Health	12	1.124	**1.084**	1.214	1.248	**0.965**	1.140	1.163	**1.099**	**0.840**	**1.103**	**1.022**
		24	1.370	**1.289**	**1.219**	1.400	**1.139**	**1.233**	1.477	**1.267**	**1.297**	1.405	**1.267**
		36	1.317	1.328	1.384	1.375	**1.307**	**1.288**	1.361	1.384	**1.283**	1.364	1.324
		48	1.389	**1.359**	**1.318**	1.530	1.427	**1.364**	**1.351**	**1.365**	1.444	**1.311**	1.473
	Security	6	124.0	124.7	126.2	**123.5**	**122.9**	126.9	124.6	126.2	127.6	126.2	128.2
		8	124.8	128.8	126.7	129.8	**121.1**	128.5	127.8	125.9	130.2	128.9	128.4
		10	129.7	**124.5**	130.5	130.7	**126.4**	**128.8**	**129.3**	**128.6**	131.4	130.6	131.4
		12	130.3	**127.0**	131.3	**128.6**	**127.5**	133.0	131.4	131.3	130.4	130.5	**126.3**
	Social Good	6	0.758	**0.687**	**0.755**	**0.737**	0.797	0.759	0.774	0.779	0.772	**0.733**	**0.728**
		8	0.767	0.777	0.867	0.803	0.861	0.846	0.779	0.876	0.864	0.839	0.792
		10	0.859	0.887	0.912	**0.852**	0.883	0.924	**0.821**	0.921	0.892	0.914	0.870
		12	0.829	0.892	0.928	0.862	0.942	0.957	0.855	0.932	0.916	0.929	0.934
	Traffic	6	0.167	0.178	**0.157**	0.184	**0.160**	0.168	**0.154**	**0.157**	**0.155**	**0.165**	**0.157**
		8	0.159	0.161	0.178	0.177	0.189	0.168	0.173	0.175	0.162	0.164	0.168
		10	0.181	0.234	0.192	**0.175**	0.194	0.211	0.191	0.192	0.183	0.181	0.213
		12	0.214	0.256	**0.211**	**0.209**	0.242	0.232	**0.205**	**0.211**	0.221	**0.200**	0.219

Table 39: Multimodal fusion strategies with **Informer** (+ **BERT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Informer	Agriculture	6	0.212	0.459	**0.168**	0.306	0.283	**0.139**	0.353	0.252	0.411	0.329	0.264
		8	0.347	0.411	0.441	**0.265**	**0.222**	**0.258**	**0.304**	**0.190**	**0.324**	**0.214**	0.416
		10	0.464	**0.226**	**0.400**	0.485	0.611	**0.269**	0.466	**0.273**	**0.324**	**0.285**	**0.320**
		12	0.579	0.634	**0.440**	**0.567**	**0.279**	**0.422**	**0.559**	**0.498**	**0.537**	**0.308**	**0.457**
	Climate	6	1.070	1.140	1.132	1.097	**1.016**	1.096	**1.032**	**1.056**	**1.044**	**1.037**	**1.040**
		8	1.081	**1.072**	1.112	1.092	**0.926**	1.086	1.083	**1.073**	1.086	**1.057**	**1.055**
		10	1.060	1.083	1.105	1.082	**0.930**	1.064	1.074	1.080	1.093	1.107	1.110
		12	1.050	1.069	1.055	1.075	**0.918**	1.067	1.057	1.124	1.087	1.076	1.111
	Economy	6	0.497	0.894	**0.335**	**0.435**	**0.480**	**0.215**	**0.449**	**0.329**	**0.479**	**0.335**	0.879
		8	0.529	0.945	**0.517**	0.572	**0.317**	0.854	0.699	0.535	**0.486**	0.560	0.585
		10	0.761	**0.071**	**0.624**	0.922	1.146	1.064	**0.642**	**0.413**	**0.724**	**0.662**	1.112
		12	1.113	**1.056**	**0.641**	**1.025**	**0.817**	1.310	**0.646**	**0.483**	**0.794**	**0.820**	**0.279**
	Energy	12	0.137	0.197	0.173	0.189	0.205	0.222	0.146	0.187	0.149	0.157	0.156
		24	0.316	**0.287**	**0.297**	0.319	**0.259**	0.323	0.321	**0.302**	0.324	0.350	0.337
		36	0.411	**0.367**	0.445	**0.393**	**0.374**	**0.368**	**0.386**	**0.364**	0.423	**0.392**	**0.370**
		48	0.483	0.492	0.495	0.561	**0.465**	**0.438**	**0.425**	**0.444**	**0.470**	**0.415**	**0.483**
	Environment	48	0.424	0.449	0.426	0.443	**0.424**	0.445	0.454	0.428	0.425	0.443	**0.420**
		96	0.437	0.491	0.486	0.464	0.458	0.468	0.458	**0.406**	**0.431**	**0.436**	**0.417**
		192	0.460	0.469	**0.434**	0.486	**0.444**	0.501	**0.430**	**0.427**	**0.449**	**0.431**	**0.412**
		336	0.460	0.492	0.476	0.483	**0.445**	**0.460**	0.485	0.488	**0.417**	**0.450**	**0.459**
	Public Health	12	1.236	**1.079**	**1.014**	**1.069**	**1.186**	**1.072**	**1.052**	**1.053**	**1.176**	**0.973**	**1.153**
		24	1.373	**1.269**	1.387	**1.367**	**1.354**	**1.223**	**1.213**	1.403	**1.250**	**1.233**	1.412
		36	1.540	**1.412**	1.572	**1.458**	**1.230**	**1.465**	**1.502**	**1.508**	**1.448**	1.559	**1.406**
		48	1.643	**1.606**	1.664	**1.626**	**1.333**	**1.493**	**1.590**	**1.523**	1.660	1.670	1.675
	Security	6	124.8	127.3	126.1	127.4	**124.8**	**122.7**	127.0	126.3	127.4	128.4	129.3
		8	126.7	128.4	127.6	129.2	128.0	128.0	**126.5**	**124.0**	**125.1**	**126.4**	**125.0**
		10	127.8	130.2	128.3	**127.4**	130.6	130.0	129.0	129.1	130.3	131.5	130.2
		12	131.1	132.4	131.1	131.8	**128.4**	131.9	**129.6**	132.1	**130.4**	**128.6**	**129.6**
	Social Good	6	0.726	**0.699**	0.746	0.732	0.760	0.741	0.731	0.765	0.731	0.727	0.750
		8	0.783	0.791	**0.782**	0.786	0.869	0.813	0.797	0.818	0.801	0.827	0.787
		10	0.825	**0.814**	0.866	0.872	**0.819**	**0.817**	0.839	0.886	0.860	0.844	0.900
		12	0.841	0.863	**0.831**	**0.840**	0.966	0.903	0.856	0.954	0.920	0.943	0.859
	Traffic	6	0.164	0.175	0.177	**0.154**	0.165	**0.160**	**0.149**	0.173	0.172	**0.152**	**0.164**
		8	0.161	0.195	0.186	0.166	0.176	0.167	0.167	0.176	0.184	0.170	0.179
		10	0.198	**0.185**	0.202	**0.190**	0.215	**0.183**	**0.187**	**0.176**	**0.175**	**0.176**	**0.186**
		12	0.225	0.227	**0.215**	**0.221**	**0.202**	**0.214**	**0.213**	**0.221**	**0.204**	**0.207**	**0.215**

Text Model: GPT-2. The following tables report the GPT-2-based results, mirroring the BERT setup with the same TS backbones, datasets, and horizons. GPT-2 provides an autoregressive Transformer encoder that contrasts with BERT's bidirectional encoder, allowing us to assess the robustness of CFA and the other constrained fusion methods to the choice of text encoder.

Table 40: Multimodal fusion strategies with **Nonstationary Transformer** (+ **GPT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Nonstationary Transformer	Agriculture	6	0.051	0.053	0.052	0.052	0.060	0.055	3.611	0.051	0.054	0.056	0.053
		8	0.071	**0.069**	**0.071**	**0.067**	0.072	**0.071**	1.243	0.072	0.071	0.073	**0.069**
		10	0.092	0.100	**0.089**	**0.088**	0.098	**0.090**	0.398	**0.091**	**0.090**	**0.091**	**0.091**
		12	0.116	0.121	0.119	**0.109**	0.121	0.120	0.353	0.118	0.128	0.119	0.116
	Climate	6	1.205	1.305	1.310	**1.172**	**1.124**	1.235	1.233	1.289	**1.185**	1.272	**1.073**
		8	1.240	**1.225**	**1.124**	**1.219**	**1.231**	1.300	**1.064**	1.289	**1.238**	**1.202**	1.250
		10	1.283	1.296	**1.275**	**1.240**	**1.217**	**1.172**	**1.059**	**1.245**	**1.224**	1.296	**1.176**
		12	1.262	**1.233**	**1.199**	**1.205**	**1.257**	**1.239**	**1.069**	**1.219**	**1.202**	**1.203**	**1.163**
	Economy	6	0.016	0.021	0.018	0.017	**0.016**	**0.016**	8.469	0.017	0.017	0.017	0.017
		8	0.018	0.020	0.019	0.020	**0.017**	0.018	8.968	**0.018**	0.019	0.019	0.020
		10	0.020	0.020	**0.019**	0.023	0.020	**0.019**	1.101	0.021	**0.019**	0.023	**0.019**
		12	0.020	0.022	**0.019**	0.022	0.022	**0.020**	1.087	0.021	0.021	**0.019**	**0.020**
	Energy	12	0.106	0.106	**0.102**	**0.099**	**0.086**	**0.100**	0.181	**0.102**	**0.094**	**0.099**	**0.101**
		24	0.159	0.205	0.210	0.206	0.207	0.188	0.555	0.208	0.166	0.179	0.186
		36	0.333	**0.312**	**0.315**	**0.324**	**0.304**	**0.282**	0.496	**0.311**	**0.304**	**0.287**	**0.306**
		48	0.391	0.461	**0.379**	0.408	0.413	0.412	0.499	**0.365**	**0.354**	**0.338**	0.404
	Environment	48	0.430	**0.428**	0.433	0.433	0.432	0.436	0.451	**0.427**	**0.425**	**0.428**	0.439
		96	0.433	0.482	**0.428**	0.434	**0.419**	0.455	0.452	0.457	0.434	0.457	0.439
		192	0.443	0.499	**0.438**	**0.442**	**0.420**	0.473	0.455	**0.430**	**0.432**	0.475	**0.436**
		336	0.438	0.472	**0.434**	**0.431**	**0.435**	0.450	0.477	0.454	0.458	**0.430**	**0.408**
	Public Health	12	0.841	**0.816**	**0.828**	0.999	**0.817**	0.911	1.209	0.858	**0.796**	**0.716**	**0.724**
		24	1.160	1.248	**0.948**	1.247	**1.102**	1.236	1.866	1.186	1.351	1.222	**1.032**
		36	1.247	1.442	**1.205**	1.298	1.432	1.442	1.619	1.361	**1.201**	1.340	1.371
		48	1.593	1.622	**1.408**	**1.301**	1.614	**1.241**	1.749	**1.541**	**1.531**	**1.343**	**1.269**
	Security	6	103.4	**102.3**	**102.0**	**100.3**	**101.3**	**101.3**	123.2	**100.6**	**100.8**	**102.3**	**99.239**
		8	104.9	106.7	105.3	105.6	106.1	105.0	123.6	**104.5**	**103.5**	**104.3**	105.3
		10	107.8	107.9	108.5	108.0	**107.5**	107.9	122.1	**107.8**	108.3	107.9	**107.8**
		12	109.3	109.7	110.0	110.2	109.5	109.4	119.5	**109.2**	**109.0**	109.4	109.7
	Social Good	6	0.790	0.811	0.811	**0.763**	0.817	**0.771**	4.397	0.810	0.828	0.799	0.793
		8	0.909	0.951	**0.880**	0.912	0.944	**0.883**	2.817	0.951	0.911	**0.899**	**0.897**
		10	1.018	**0.963**	**0.979**	**0.947**	1.045	**0.983**	1.095	1.071	**0.933**	**0.987**	**0.928**
		12	1.073	1.165	**1.038**	**0.997**	1.075	1.150	**1.071**	1.169	1.102	1.098	**1.020**
	Traffic	6	0.182	0.183	**0.171**	**0.180**	**0.178**	**0.171**	0.876	0.186	0.187	**0.174**	**0.172**
		8	0.185	**0.184**	0.188	0.194	0.202	0.191	0.622	0.190	**0.185**	**0.185**	**0.180**
		10	0.187	0.191	**0.187**	0.191	0.198	0.189	0.223	0.189	0.189	0.191	0.187
		12	0.243	0.254	0.253	0.251	**0.240**	**0.240**	0.269	0.251	0.243	**0.242**	**0.243**

Table 41: Multimodal fusion strategies with **Koopa** (+ **GPT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	CFA
Koopa	Agriculture	6	0.059	**0.056**	**0.058**	**0.058**	5.693	3.044	3.044	0.060	0.067	**0.055**	**0.056**
		8	0.077	0.078	**0.072**	**0.072**	0.173	0.108	0.108	**0.076**	0.092	**0.073**	**0.076**
		10	0.099	**0.091**	**0.090**	**0.090**	0.426	0.624	0.624	0.100	0.127	**0.091**	0.100
		12	0.129	**0.119**	**0.117**	**0.117**	1.032	1.233	1.233	0.131	0.155	**0.117**	**0.128**
	Climate	6	1.251	6.593	1.258	1.258	4.140	**1.219**	**1.219**	1.277	**1.069**	1.253	1.253
		8	1.264	1.499	**1.261**	**1.261**	**1.192**	**1.122**	**1.122**	1.291	**1.057**	**1.262**	**1.258**
		10	1.247	3.355	1.254	1.254	1.404	**1.045**	**1.045**	1.296	**1.112**	**1.243**	1.247
		12	1.232	1.254	1.252	1.252	**1.187**	**1.191**	**1.191**	1.260	**1.070**	1.242	1.232
	Economy	6	0.021	0.033	0.027	0.027	13.556	16.346	16.346	0.028	0.044	0.026	**0.017**
		8	0.017	0.018	0.020	0.020	0.628	0.540	0.540	0.024	0.072	0.018	0.018
		10	0.017	0.022	0.027	0.027	3.752	3.152	3.152	0.027	0.064	0.018	**0.017**
		12	0.018	0.028	0.028	0.028	0.304	15.139	15.139	0.027	0.085	0.022	0.018
	Energy	12	0.107	2140.3	0.108	0.108	56.945	0.156	0.156	0.117	0.109	0.110	0.107
		24	0.216	0.256	**0.209**	**0.209**	283.8	0.384	0.384	0.234	0.216	**0.199**	**0.205**
		36	0.300	**0.284**	**0.296**	**0.296**	1.199	0.553	0.553	0.310	**0.296**	**0.296**	**0.299**
		48	0.388	4008.7	0.397	0.397	2.901	1.672	1.672	0.428	0.410	0.392	0.402
	Environment	48	0.482	271860512.0	**0.455**	**0.455**	53946020.0	**0.451**	**0.451**	0.488	**0.449**	**0.476**	**0.481**
		96	0.526	488845344.0	**0.492**	**0.492**	3337.4	**0.484**	**0.484**	0.538	**0.454**	**0.490**	0.536
		192	0.567	1306404992.0	**0.524**	**0.524**	284732.7	**0.490**	**0.490**	**0.565**	**0.483**	**0.510**	**0.564**
		336	0.525	82270.4	0.535	0.535	80511.4	**0.496**	**0.496**	0.530	**0.490**	**0.523**	0.528
	Public Health	12	1.029	1297.5	**0.995**	**0.995**	36.918	**1.015**	**1.015**	1.269	1.233	**0.915**	**1.008**
		24	1.402	**1.145**	**1.152**	**1.152**	1.983	**1.242**	**1.242**	1.546	**1.379**	**1.188**	1.410
		36	1.614	**1.287**	**1.259**	**1.259**	2.083	**1.532**	**1.532**	1.762	**1.311**	**1.283**	1.625
		48	1.728	**1.478**	**1.378**	**1.378**	1.793	1.950	1.950	1.871	**1.455**	**1.362**	**1.715**
	Security	6	105.1	**97.736**	**103.4**	**103.4**	136.4	140.4	140.4	**104.9**	109.3	**103.5**	**104.5**
		8	109.1	**106.4**	111.6	111.6	110.4	110.4	110.4	113.7	113.0	**107.2**	**105.5**
		10	108.8	**100.8**	**108.8**	**108.8**	117.7	118.3	118.3	110.6	111.6	108.8	**108.7**
		12	111.3	**109.4**	**110.3**	**110.3**	158.4	149.1	149.1	113.0	116.9	**110.2**	**109.4**
	Social Good	6	0.849	0.854	0.869	0.869	3.863	3.757	3.757	**0.847**	**0.739**	**0.793**	0.849
		8	0.931	1.195	**0.911**	**0.911**	**0.929**	0.962	0.962	0.939	**0.849**	**0.877**	**0.914**
		10	0.985	1.145	1.005	1.005	1.291	1.245	1.245	0.998	**0.859**	**0.895**	0.994
		12	1.078	**1.045**	**1.059**	**1.059**	3.136	2.738	2.738	**1.060**	**0.889**	**1.020**	1.079
	Traffic	6	0.226	0.280	**0.221**	**0.221**	1.695	1.863	1.863	0.245	0.238	0.232	**0.196**
		8	0.214	**0.213**	0.225	0.225	**0.204**	**0.213**	**0.213**	0.227	0.219	**0.211**	**0.207**
		10	0.216	0.223	0.224	0.224	0.653	0.498	0.498	0.224	0.218	0.221	**0.209**
		12	0.274	0.337	0.285	0.285	2.742	1.386	1.386	0.280	0.277	0.283	**0.269**

Table 42: Multimodal fusion strategies with **DLinear** (+ **GPT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
DLinear	Agriculture	6	0.114	0.127	0.134	0.132	0.575	0.320	0.454	0.135	0.233	0.133	**0.085**
		8	0.324	**0.182**	**0.185**	**0.181**	0.973	2.019	1.390	**0.206**	**0.217**	**0.223**	**0.099**
		10	0.163	0.203	0.204	0.204	0.481	0.419	0.199	0.178	0.208	0.205	**0.127**
		12	0.217	0.239	0.240	0.242	0.428	0.350	0.326	**0.162**	0.410	**0.180**	**0.183**
	Climate	6	1.198	1.277	1.229	1.203	1.308	1.252	1.219	1.306	**1.084**	1.241	**1.090**
		8	1.364	**1.318**	**1.267**	**1.247**	**1.250**	**1.064**	**1.162**	**1.328**	**1.071**	**1.241**	**1.090**
		10	1.166	1.312	1.333	1.285	1.181	**1.101**	**1.105**	1.289	**1.105**	1.305	**1.116**
		12	1.174	1.343	1.321	1.289	**1.156**	**1.117**	**1.122**	1.290	**1.096**	1.257	**1.098**
	Economy	6	0.090	0.092	0.098	0.097	18.033	13.749	13.121	0.107	0.345	0.109	**0.024**
		8	0.233	**0.129**	**0.143**	**0.143**	12.672	12.211	12.812	**0.131**	0.274	**0.153**	**0.025**
		10	0.086	0.123	0.130	0.131	2.683	2.407	2.495	0.102	0.260	0.151	**0.051**
		12	0.109	0.128	0.130	0.129	1.884	1.555	2.258	**0.064**	0.576	**0.091**	**0.060**
	Energy	12	0.115	0.193	0.155	0.140	0.224	0.170	0.154	0.132	**0.113**	0.131	**0.096**
		24	0.219	0.283	0.259	0.259	0.793	0.287	0.280	0.262	0.299	0.225	**0.201**
		36	0.303	0.347	0.322	0.322	0.585	0.346	0.341	0.322	0.365	0.369	**0.284**
		48	0.415	0.474	0.438	0.458	0.674	0.693	0.679	0.439	0.460	0.458	**0.391**
	Environment	48	0.490	**0.433**	**0.438**	**0.439**	**0.466**	**0.447**	**0.444**	0.495	**0.442**	**0.443**	**0.489**
		96	0.568	**0.506**	**0.492**	**0.473**	**0.539**	**0.493**	**0.494**	0.570	**0.461**	**0.478**	0.572
		192	0.583	**0.516**	**0.501**	**0.495**	**0.571**	0.589	0.614	0.585	**0.528**	**0.502**	0.587
		336	0.538	**0.511**	**0.488**	**0.484**	**0.518**	**0.483**	**0.487**	**0.536**	**0.490**	**0.481**	0.538
	Public Health	12	1.330	1.360	1.403	1.340	1.527	1.552	1.482	1.545	1.334	1.430	**1.228**
		24	1.578	**1.505**	1.654	**1.571**	2.005	1.709	1.663	1.677	1.690	**1.527**	1.589
		36	1.619	1.637	1.676	1.657	2.112	1.689	1.644	1.740	1.691	1.662	1.622
		48	1.691	1.714	1.749	1.734	1.963	1.822	1.779	1.765	1.727	**1.612**	**1.674**
	Security	6	104.4	105.1	104.9	**104.3**	189.4	169.6	167.0	105.7	105.9	104.6	104.8
		8	109.2	109.7	**107.8**	**107.8**	153.0	151.1	147.8	110.6	**107.9**	**108.1**	**109.0**
		10	110.5	113.3	111.8	111.3	113.2	112.8	113.0	110.6	111.2	**110.4**	**109.7**
		12	112.0	114.9	113.3	112.5	113.3	113.3	113.2	113.0	114.6	112.8	**111.7**
	Social Good	6	0.817	0.895	0.907	0.874	2.990	1.969	1.903	0.893	0.928	0.853	**0.779**
		8	0.885	1.146	1.009	1.142	2.403	2.138	2.032	0.942	0.946	0.913	**0.870**
		10	1.026	1.050	1.090	**1.012**	1.074	**0.954**	**0.959**	1.141	**0.983**	1.121	**0.966**
		12	1.010	1.136	1.133	1.071	1.144	**1.003**	1.031	1.068	1.040	1.082	**1.003**
	Traffic	6	0.254	0.289	0.313	0.294	2.952	2.158	2.659	0.285	0.367	0.290	**0.227**
		8	0.322	0.322	0.349	0.327	2.278	2.012	2.147	**0.270**	0.324	0.339	**0.224**
		10	0.243	0.323	0.345	0.331	0.646	0.316	0.568	0.264	0.315	0.341	**0.219**
		12	0.287	0.342	0.381	0.368	0.549	0.545	0.364	0.307	0.365	0.319	**0.261**

Table 43: Multimodal fusion strategies with **iTransformer** (+ **GPT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
iTransformer	Agriculture	6	0.059	0.060	0.061	**0.058**	0.062	**0.058**	1.273	**0.059**	0.060	0.059	**0.059**
		8	0.076	0.078	0.081	**0.072**	**0.076**	0.077	1.097	0.081	0.080	0.079	**0.076**
		10	0.097	0.103	0.101	**0.090**	0.097	0.099	0.347	0.101	0.103	0.098	0.098
		12	0.128	0.129	0.129	**0.118**	0.128	0.131	0.390	0.128	0.131	0.129	**0.127**
	Climate	6	1.100	1.189	1.140	1.128	1.130	1.141	1.326	1.141	1.130	1.150	1.115
		8	1.178	1.204	1.203	1.193	**1.162**	1.193	**1.158**	1.202	1.231	1.197	1.227
		10	1.186	1.200	1.201	1.188	**1.174**	1.248	**1.038**	1.200	1.204	1.226	1.206
		12	1.176	**1.174**	**1.163**	1.181	1.197	1.182	**1.035**	**1.154**	1.191	1.198	1.183
	Economy	6	0.015	**0.015**	**0.015**	0.020	**0.015**	0.015	15.774	**0.015**	0.016	**0.015**	**0.014**
		8	0.015	0.016	**0.015**	0.021	**0.015**	0.016	10.479	0.015	0.016	0.016	**0.015**
		10	0.015	0.016	**0.015**	0.017	**0.015**	0.016	1.191	**0.015**	**0.015**	0.016	**0.015**
		12	0.016	**0.016**	**0.016**	0.018	**0.015**	**0.016**	1.192	**0.016**	**0.016**	**0.016**	**0.016**
	Energy	12	0.111	**0.108**	**0.102**	**0.111**	**0.107**	**0.111**	0.214	**0.102**	**0.107**	**0.107**	**0.111**
		24	0.228	**0.227**	0.230	**0.221**	**0.227**	**0.221**	0.672	**0.205**	**0.216**	0.228	0.231
		36	0.302	**0.283**	0.318	**0.278**	**0.274**	0.311	1.301	**0.294**	0.317	**0.295**	0.307
		48	0.408	**0.402**	**0.405**	**0.403**	**0.374**	0.414	0.709	**0.403**	**0.395**	**0.388**	**0.380**
	Environment	48	0.411	**0.401**	**0.408**	0.425	**0.404**	**0.408**	0.451	**0.410**	**0.407**	**0.405**	**0.410**
		96	0.418	**0.406**	0.429	0.446	**0.418**	0.422	0.510	0.432	0.425	**0.413**	0.420
		192	0.435	**0.432**	**0.422**	0.463	**0.421**	0.437	0.536	0.438	0.436	**0.430**	**0.430**
		336	0.418	**0.416**	0.427	0.441	**0.413**	0.422	**0.415**	0.427	0.425	0.419	0.424
	Public Health	12	1.023	**0.966**	1.044	**0.965**	1.071	**0.981**	**0.991**	1.048	**0.987**	**0.940**	1.043
		24	1.438	1.465	1.455	**1.226**	1.445	**1.433**	1.599	1.453	1.464	1.448	**1.437**
		36	1.637	1.647	**1.625**	**1.291**	1.676	**1.620**	1.883	**1.623**	**1.635**	**1.627**	**1.628**
		48	1.738	1.749	**1.737**	**1.457**	1.790	**1.711**	1.906	**1.735**	1.749	1.751	1.747
	Security	6	104.9	**104.2**	**102.5**	112.7	**102.7**	**103.2**	134.4	**100.8**	**104.0**	**102.8**	105.1
		8	108.7	**106.8**	**106.3**	113.1	**105.8**	**106.1**	134.6	**107.4**	**106.5**	**106.4**	108.9
		10	111.4	112.4	**107.8**	**109.6**	**109.3**	**109.0**	122.4	**108.2**	**109.1**	**108.4**	**110.8**
		12	114.0	**111.1**	**110.0**	119.3	**111.1**	**110.6**	118.6	**111.2**	**112.6**	**111.7**	**111.1**
	Social Good	6	0.830	**0.828**	0.832	**0.782**	0.832	0.859	4.210	0.832	**0.827**	**0.829**	**0.811**
		8	0.961	**0.951**	0.970	**0.893**	**0.924**	**0.960**	2.405	0.970	**0.939**	0.967	**0.945**
		10	1.061	1.066	1.062	**0.987**	1.063	**1.056**	1.128	1.062	**0.946**	**1.053**	**1.060**
		12	1.144	1.162	1.168	**1.076**	**1.130**	1.171	**1.123**	1.169	**1.139**	**1.139**	**1.125**
	Traffic	6	0.179	0.187	0.180	0.187	0.202	0.188	1.668	0.182	**0.176**	0.179	**0.176**
		8	0.185	0.188	0.187	0.197	0.189	0.202	1.946	0.187	**0.184**	**0.178**	0.189
		10	0.195	**0.195**	**0.194**	0.199	**0.194**	0.196	0.411	**0.188**	**0.191**	**0.187**	0.197
		12	0.249	**0.248**	0.251	0.255	0.250	0.251	0.265	0.252	0.252	**0.232**	**0.238**

Table 44: Multimodal fusion strategies with **PatchTST** (+ **GPT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
PatchTST	Agriculture	6	0.058	0.059	0.060	**0.056**	0.059	0.060	1.357	0.059	0.060	0.060	0.058
		8	0.078	0.078	0.080	**0.074**	0.078	0.079	0.816	**0.078**	0.079	0.079	**0.077**
		10	0.100	**0.098**	0.101	**0.093**	**0.098**	0.101	0.382	0.101	0.101	0.101	0.100
		12	0.132	**0.129**	**0.129**	**0.122**	**0.129**	**0.128**	0.371	**0.129**	**0.131**	**0.127**	**0.129**
	Climate	6	1.257	**1.234**	**1.238**	**1.235**	**1.234**	**1.253**	1.332	**1.238**	**1.248**	**1.215**	**1.230**
		8	1.265	**1.255**	**1.224**	**1.257**	**1.255**	**1.249**	**1.183**	**1.224**	**1.252**	**1.233**	**1.236**
		10	1.274	1.276	**1.256**	**1.264**	1.276	**1.267**	**1.092**	**1.256**	**1.262**	**1.248**	1.276
		12	1.239	1.248	1.242	1.254	1.248	1.255	**1.090**	1.242	1.264	1.240	1.251
	Economy	6	0.016	0.016	0.017	0.020	0.016	0.017	17.735	0.016	0.017	0.017	0.016
		8	0.017	**0.017**	0.019	0.019	**0.017**	**0.017**	10.180	0.019	0.017	0.017	0.017
		10	0.017	0.017	0.017	0.021	0.017	0.017	1.351	0.017	0.017	0.017	0.017
		12	0.017	0.018	0.018	0.019	0.018	0.017	1.250	0.018	0.018	0.018	0.018
	Energy	12	0.105	**0.102**	0.110	0.109	**0.102**	0.108	0.193	0.110	0.112	0.108	0.113
		24	0.226	0.227	**0.222**	**0.219**	0.227	**0.223**	0.606	**0.222**	**0.224**	**0.215**	**0.213**
		36	0.310	**0.302**	**0.306**	**0.299**	**0.302**	0.317	1.074	**0.305**	0.319	0.316	**0.305**
		48	0.414	0.430	0.424	**0.409**	0.430	0.415	0.557	0.424	0.417	0.419	0.415
	Environment	48	0.459	0.461	**0.457**	**0.451**	0.461	**0.459**	0.469	0.462	**0.456**	**0.454**	0.462
		96	0.504	**0.496**	**0.503**	**0.486**	**0.496**	0.508	0.563	**0.459**	**0.493**	**0.471**	**0.475**
		192	0.542	**0.541**	**0.531**	**0.494**	**0.541**	**0.540**	0.604	**0.539**	**0.539**	**0.519**	**0.507**
		336	0.509	**0.500**	0.511	**0.507**	**0.500**	0.512	**0.476**	**0.507**	0.513	**0.503**	**0.479**
	Public Health	12	0.913	**0.891**	0.914	**0.849**	**0.891**	0.919	1.089	0.914	**0.908**	**0.881**	**0.901**
		24	1.391	**1.316**	**1.289**	**1.158**	**1.316**	**1.349**	1.720	**1.379**	1.400	**1.330**	**1.364**
		36	1.623	**1.620**	**1.606**	**1.362**	**1.620**	1.624	**1.463**	**1.605**	**1.611**	**1.616**	**1.607**
		48	1.724	1.727	1.730	**1.473**	1.727	**1.718**	1.799	1.730	1.724	1.727	1.743
	Security	6	104.5	**104.3**	**102.9**	105.5	**104.3**	**103.3**	142.8	**103.2**	104.6	104.7	**104.5**
		8	110.1	**109.6**	**105.8**	**104.7**	**109.6**	**106.3**	137.9	**106.8**	**108.1**	**107.3**	**107.2**
		10	113.3	**109.9**	**108.8**	**110.5**	**109.9**	**108.8**	119.7	**108.1**	**109.8**	**108.9**	**110.8**
		12	109.8	111.4	110.1	111.0	111.4	111.7	119.3	110.1	110.6	112.1	113.7
	Social Good	6	0.800	0.802	**0.787**	**0.764**	0.802	**0.785**	4.051	**0.788**	0.802	**0.792**	**0.770**
		8	0.894	**0.891**	**0.886**	**0.840**	**0.891**	**0.881**	2.800	**0.885**	0.909	0.899	**0.880**
		10	1.030	1.031	1.051	**0.960**	1.031	1.051	1.090	1.051	**1.014**	1.046	**1.010**
		12	1.126	**1.118**	**1.087**	**1.014**	**1.118**	**1.077**	**1.089**	**1.085**	**1.105**	**1.076**	**1.059**
	Traffic	6	0.184	**0.181**	0.184	**0.179**	**0.181**	0.188	1.819	**0.183**	0.188	**0.172**	**0.171**
		8	0.181	**0.178**	0.185	0.193	**0.178**	0.190	1.937	**0.178**	0.185	**0.181**	**0.177**
		10	0.189	**0.188**	**0.184**	0.201	**0.188**	0.201	0.443	0.191	**0.188**	**0.183**	**0.182**
		12	0.238	0.244	0.253	0.253	0.244	0.245	0.434	**0.235**	0.241	0.242	0.257

Table 45: Multimodal fusion strategies with **FEDformer** (+ **GPT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
FEDformer	Agriculture	6	0.060	0.063	0.064	**0.058**	0.062	**0.058**	1.314	0.063	**0.057**	0.061	**0.054**
		8	0.072	0.075	0.074	0.076	0.079	**0.068**	1.026	0.072	0.073	**0.071**	**0.069**
		10	0.099	**0.096**	**0.090**	**0.091**	0.104	**0.096**	0.278	**0.089**	**0.089**	**0.089**	**0.090**
		12	0.117	**0.113**	0.120	0.118	0.124	0.119	0.435	0.118	0.120	0.123	0.117
	Climate	6	1.116	1.155	**1.093**	1.141	**1.071**	**1.085**	1.242	**1.093**	**1.066**	**1.055**	**1.058**
		8	1.082	**1.071**	**1.057**	**1.078**	**1.077**	**1.050**	**1.052**	**1.057**	**1.049**	**1.076**	**1.044**
		10	1.105	1.109	1.124	**1.102**	**1.054**	1.112	**0.898**	1.124	1.113	**1.094**	**1.068**
		12	1.084	1.116	1.104	1.106	1.134	**1.061**	**0.924**	1.106	1.114	1.094	1.092
	Economy	6	0.039	0.060	0.047	**0.027**	0.041	0.045	7.623	**0.026**	**0.030**	**0.033**	0.046
		8	0.047	0.053	0.051	0.055	**0.029**	0.049	7.812	**0.045**	**0.045**	**0.046**	**0.040**
		10	0.037	0.051	0.047	0.039	0.052	**0.034**	1.619	0.047	0.040	0.053	0.044
		12	0.044	0.046	**0.040**	0.054	0.045	**0.038**	1.455	**0.040**	**0.042**	**0.034**	**0.041**
	Energy	12	0.097	0.103	**0.091**	**0.097**	0.111	**0.095**	0.131	**0.091**	**0.097**	**0.092**	**0.093**
		24	0.177	0.184	0.181	0.177	0.183	0.179	1.130	0.181	**0.175**	**0.175**	0.179
		36	0.254	0.296	0.263	**0.251**	0.346	**0.254**	0.726	0.256	**0.253**	0.254	0.254
		48	0.367	0.384	0.404	**0.363**	0.416	**0.357**	1.225	0.451	**0.366**	**0.365**	**0.356**
	Environment	48	0.484	**0.471**	**0.472**	**0.463**	**0.481**	**0.430**	**0.473**	**0.483**	**0.475**	**0.450**	**0.459**
		96	0.488	0.514	0.517	0.501	0.498	**0.482**	**0.419**	0.516	0.536	0.518	0.493
		192	0.482	0.513	0.528	0.497	0.528	0.549	**0.476**	0.528	0.505	0.505	0.502
		336	0.466	0.470	**0.466**	0.481	**0.463**	**0.464**	**0.438**	0.469	0.477	0.477	**0.445**
	Public Health	12	1.050	1.068	1.084	1.089	1.168	**1.024**	1.071	1.087	1.089	1.063	1.063
		24	1.488	**1.449**	**1.311**	**1.348**	1.529	**1.367**	**1.449**	**1.379**	**1.383**	**1.409**	**1.385**
		36	1.419	1.568	1.554	1.518	1.492	1.492	1.927	1.435	1.421	1.493	1.466
		48	1.499	1.599	1.582	1.602	1.736	1.521	1.564	1.543	1.617	1.512	**1.481**
	Security	6	105.9	110.0	106.1	**102.3**	106.1	107.9	170.2	**104.4**	**103.8**	110.1	107.3
		8	109.1	**108.0**	109.6	**108.7**	110.3	109.8	142.9	109.7	110.0	**107.4**	**106.8**
		10	113.8	**112.3**	**111.6**	**110.9**	**112.4**	116.2	**113.7**	**111.6**	**113.3**	**108.2**	**113.3**
		12	117.2	**116.9**	**114.8**	**114.8**	**114.7**	117.4	**116.7**	**114.8**	**115.6**	**111.2**	**114.3**
	Social Good	6	0.874	0.886	**0.807**	**0.822**	**0.861**	**0.862**	1.783	**0.806**	**0.773**	**0.793**	**0.839**
		8	0.919	**0.857**	**0.884**	**0.857**	**0.900**	**0.855**	1.962	**0.883**	**0.873**	**0.883**	**0.853**
		10	0.914	0.931	**0.895**	0.919	1.044	0.934	0.961	**0.895**	**0.903**	0.919	0.927
		12	1.015	**0.977**	**0.994**	**0.960**	1.108	**1.000**	1.117	**0.993**	**0.973**	**0.986**	**0.977**
	Traffic	6	0.149	0.156	0.151	0.158	**0.146**	0.153	2.007	0.161	0.155	0.150	0.153
		8	0.152	0.158	**0.151**	0.160	**0.144**	0.158	1.351	**0.151**	0.154	0.154	0.159
		10	0.166	0.173	**0.163**	**0.166**	**0.146**	**0.160**	0.292	**0.164**	**0.162**	**0.159**	**0.157**
		12	0.224	0.229	0.229	0.240	**0.213**	**0.213**	0.428	0.232	**0.223**	**0.221**	0.230

Table 46: Multimodal fusion strategies with **FiLM** (+ **GPT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	CFA
FiLM	Agriculture	6	0.061	0.103	0.062	0.064	2.776	0.062	4.712	0.064	0.064	0.061	0.063
		8	0.082	0.200	**0.081**	**0.080**	2.550	0.087	1.179	**0.080**	**0.080**	**0.080**	**0.078**
		10	0.105	0.182	**0.105**	**0.100**	0.149	0.109	0.337	0.105	0.107	**0.103**	**0.103**
		12	0.143	**0.142**	**0.133**	**0.123**	1.022	**0.136**	0.465	**0.133**	**0.136**	**0.136**	**0.132**
	Climate	6	1.305	**1.274**	**1.282**	**1.268**	1.427	**1.266**	1.320	**1.270**	**1.287**	**1.233**	**1.254**
		8	1.282	**1.273**	**1.268**	**1.268**	**1.069**	1.292	**1.099**	1.313	**1.263**	**1.255**	**1.264**
		10	1.278	9.623	**1.274**	1.280	7.707	1.290	**1.097**	1.286	1.285	**1.272**	**1.273**
		12	1.280	10.115	**1.280**	1.289	1.882	1.291	**1.110**	1.301	1.281	1.311	**1.264**
	Economy	6	0.017	0.065	0.026	0.035	23.248	0.021	20.595	0.019	0.018	0.019	0.017
		8	0.018	0.048	0.020	0.020	14.450	0.020	13.853	**0.017**	**0.017**	**0.018**	0.018
		10	0.019	0.039	0.020	0.019	0.039	0.020	2.648	**0.019**	**0.018**	**0.018**	**0.018**
		12	0.018	7.453	0.023	0.045	1.776	0.021	2.441	**0.018**	**0.018**	0.018	**0.018**
	Energy	12	0.119	2575.9	**0.117**	0.121	0.402	0.133	0.178	**0.104**	**0.103**	**0.108**	**0.102**
		24	0.229	0.340	0.250	0.259	0.747	0.252	0.791	**0.211**	**0.216**	**0.228**	**0.206**
		36	0.302	0.382	0.333	0.328	1.555	0.339	1.447	0.303	0.318	0.315	**0.300**
		48	0.435	0.483	**0.431**	0.453	0.673	0.481	0.645	**0.419**	**0.430**	0.437	**0.429**
	Environment	48	0.488	177523232.0	**0.479**	**0.471**	0.498	**0.477**	0.515	0.490	**0.444**	**0.448**	0.490
		96	0.546	36514.0	0.547	**0.490**	0.582	**0.537**	0.608	0.546	**0.542**	**0.480**	**0.540**
		192	0.574	985353600.0	0.576	**0.542**	0.587	**0.561**	0.615	**0.573**	**0.569**	**0.573**	**0.570**
		336	0.529	0.599	**0.514**	**0.519**	0.539	0.531	**0.481**	**0.526**	**0.500**	**0.528**	**0.527**
	Public Health	12	1.155	2890.2	1.191	**1.142**	2.007	1.271	1.219	**1.117**	**1.130**	**1.122**	**1.106**
		24	1.492	**1.435**	1.496	**1.339**	2.784	1.643	1.841	**1.453**	1.494	**1.474**	**1.432**
		36	1.635	1.779	**1.632**	1.838	2.019	1.681	2.346	1.873	1.658	1.660	1.685
		48	1.722	2.053	1.796	2.035	1.998	1.780	1.824	**1.722**	1.746	1.761	1.739
	Security	6	124.2	**105.9**	**102.1**	**100.9**	208.1	**103.5**	191.0	**102.8**	**101.6**	**102.3**	**107.1**
		8	113.8	116.7	**106.5**	116.5	151.0	**105.7**	163.2	**109.3**	**105.1**	**106.3**	**105.1**
		10	117.0	135.0	**109.3**	133.5	**97.995**	**108.1**	**111.9**	**109.4**	**108.3**	**109.1**	**114.0**
		12	119.0	134.6	**110.0**	**108.1**	**96.776**	**110.3**	**113.2**	132.4	**113.1**	**110.9**	**113.8**
	Social Good	6	0.900	49.855	**0.831**	**0.822**	3.632	**0.840**	3.854	**0.820**	**0.798**	**0.835**	**0.818**
		8	0.994	1.101	0.998	1.049	2.161	**0.971**	2.346	1.000	**0.953**	**0.945**	**0.967**
		10	1.119	114.0	**1.031**	1.191	123.0	**1.107**	**1.115**	**1.014**	1.137	**1.059**	1.123
		12	1.216	280.3	**1.087**	**1.090**	90.555	**1.185**	**1.080**	1.248	1.237	**1.159**	**1.165**
	Traffic	6	0.229	0.285	0.234	0.252	4.318	0.235	3.520	0.256	0.233	0.234	0.236
		8	0.223	0.226	**0.220**	**0.221**	0.682	0.230	2.414	0.230	0.228	**0.219**	0.233
		10	0.216	0.224	0.217	**0.215**	0.396	0.219	0.557	0.241	0.228	0.217	**0.215**
		12	0.253	0.515	0.261	0.270	0.269	0.267	0.526	0.283	0.262	0.271	**0.251**

Table 47: Multimodal fusion strategies with **TiDE** (+ **GPT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
TiDE	Agriculture	6	0.071	**0.069**	0.082	**0.069**	1.152	**0.065**	1.159	**0.063**	**0.063**	**0.062**	**0.060**
		8	0.091	**0.090**	0.092	**0.091**	1.226	0.093	1.179	**0.082**	**0.082**	**0.080**	**0.082**
		10	0.112	7.192	**0.110**	0.112	11.723	0.120	0.435	**0.103**	**0.104**	**0.104**	**0.103**
		12	0.160	8.039	**0.144**	**0.135**	14.564	**0.150**	0.405	**0.135**	**0.134**	**0.134**	**0.135**
	Climate	6	1.456	1.577	1.606	1.576	1.491	**1.418**	**1.363**	**1.252**	**1.244**	**1.239**	**1.258**
		8	1.469	1.555	1.481	**1.446**	**1.048**	1.532	**1.172**	**1.264**	**1.274**	**1.258**	**1.267**
		10	1.419	11.502	1.467	1.477	2.938	1.561	**1.184**	**1.274**	**1.272**	**1.259**	**1.259**
		12	1.467	3.924	**1.395**	**1.449**	2.043	1.508	**1.154**	**1.255**	**1.278**	**1.264**	**1.274**
	Economy	6	0.034	0.051	0.039	0.049	20.604	0.044	20.206	**0.017**	**0.017**	**0.017**	**0.017**
		8	0.049	**0.040**	**0.035**	**0.041**	13.386	**0.031**	13.664	**0.017**	**0.018**	**0.017**	**0.018**
		10	0.029	5.048	0.031	0.040	10.335	0.040	2.467	**0.018**	**0.017**	**0.017**	**0.017**
		12	0.033	5.311	**0.031**	0.035	4.536	0.038	2.391	**0.018**	**0.018**	**0.019**	**0.017**
	Energy	12	0.135	2110.5	0.139	**0.133**	740.5	**0.134**	0.199	**0.115**	**0.115**	**0.108**	**0.112**
		24	0.240	0.353	0.244	0.262	0.725	0.243	0.752	**0.212**	**0.210**	**0.217**	**0.220**
		36	0.323	5843.1	0.333	**0.321**	2234.7	0.332	1.525	**0.294**	**0.307**	**0.305**	**0.300**
		48	0.442	0.468	0.443	**0.430**	0.624	**0.442**	0.631	**0.403**	**0.414**	**0.407**	**0.408**
	Environment	48	0.483	0.955	0.485	**0.442**	0.502	0.485	0.519	0.485	0.483	0.485	0.484
		96	0.543	**0.513**	**0.542**	**0.512**	0.576	**0.539**	0.636	**0.541**	**0.539**	**0.539**	**0.540**
		192	0.576	13991.8	0.578	0.586	13866.6	0.577	0.689	0.577	0.577	0.577	**0.576**
		336	0.533	22627.6	0.534	**0.507**	4743.0	0.533	**0.482**	0.534	0.533	0.533	0.534
	Public Health	12	1.300	182.9	1.320	**1.295**	240.6	1.329	1.396	**1.076**	**1.128**	**1.113**	**1.106**
		24	1.520	2.213	**1.499**	1.605	1.908	1.567	1.901	**1.432**	**1.434**	**1.448**	**1.425**
		36	1.670	2374.3	**1.668**	1.731	1646.7	**1.669**	2.276	**1.605**	**1.619**	**1.617**	**1.602**
		48	1.787	1.970	**1.756**	1.822	2.018	1.788	1.910	**1.724**	**1.723**	**1.726**	**1.740**
	Security	6	146.1	**123.9**	**134.9**	**124.6**	201.4	**122.2**	191.0	**105.2**	**107.2**	**107.6**	**107.5**
		8	129.7	137.7	132.5	137.5	154.3	**128.9**	156.5	**108.3**	**108.9**	**112.4**	**109.4**
		10	132.3	147.6	135.2	133.5	**96.384**	135.4	**117.7**	**112.7**	**110.6**	**114.6**	**111.9**
		12	145.3	**144.8**	**139.2**	**138.9**	**107.5**	**142.4**	**120.8**	**112.7**	**112.3**	**112.3**	**111.7**
	Social Good	6	0.955	**0.928**	1.036	**0.943**	3.995	0.970	3.955	**0.835**	**0.836**	**0.823**	**0.843**
		8	1.037	1.100	**1.013**	1.098	2.476	1.044	2.711	**0.950**	**0.940**	**0.950**	**0.947**
		10	1.210	134.7	**1.097**	**1.168**	70.622	1.243	**0.982**	**1.071**	**1.070**	**1.109**	**1.068**
		12	1.415	156.6	**1.186**	**1.298**	57.431	**1.205**	**1.075**	**1.162**	**1.252**	**1.183**	**1.147**
	Traffic	6	0.293	0.317	**0.285**	0.317	3.595	0.301	3.130	**0.236**	**0.235**	**0.236**	**0.233**
		8	0.309	**0.306**	**0.277**	**0.301**	0.962	**0.272**	2.299	**0.236**	**0.236**	**0.234**	**0.224**
		10	0.251	11.396	**0.245**	0.320	6.953	0.302	0.641	**0.224**	**0.231**	**0.225**	**0.229**
		12	0.319	13.832	**0.308**	0.328	8.802	0.334	0.585	**0.288**	**0.290**	**0.284**	**0.289**

Table 48: Multimodal fusion strategies with **Autoformer** (+ **GPT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Autoformer	Agriculture	6	0.072	**0.072**	**0.065**	**0.063**	**0.071**	**0.062**	1.291	**0.065**	**0.068**	**0.066**	**0.061**
		8	0.083	**0.082**	0.094	**0.080**	0.089	**0.070**	1.244	**0.082**	0.094	**0.079**	0.089
		10	0.112	**0.106**	**0.105**	**0.097**	**0.109**	**0.096**	0.393	**0.104**	**0.110**	**0.100**	**0.097**
		12	0.136	0.140	0.139	**0.129**	0.141	**0.134**	0.505	**0.125**	**0.132**	**0.128**	**0.130**
	Climate	6	1.240	1.278	1.248	**1.222**	**1.168**	**1.192**	1.266	1.244	1.248	**1.206**	**1.225**
		8	1.200	1.234	1.265	**1.199**	**1.180**	**1.168**	**1.122**	1.241	**1.162**	**1.132**	**1.179**
		10	1.247	1.250	**1.218**	1.249	1.291	**1.169**	**1.025**	**1.210**	**1.208**	**1.211**	**1.211**
		12	1.177	1.208	1.199	1.265	**1.134**	1.188	**0.965**	1.249	1.201	1.195	1.178
	Economy	6	0.060	0.069	0.061	**0.058**	0.080	**0.055**	14.606	0.066	**0.053**	0.071	0.066
		8	0.070	**0.066**	**0.059**	**0.055**	**0.067**	**0.063**	10.478	**0.059**	**0.064**	**0.051**	**0.040**
		10	0.060	0.064	**0.056**	**0.033**	0.075	**0.047**	1.743	**0.043**	**0.058**	0.062	0.062
		12	0.061	0.067	**0.053**	**0.058**	0.072	**0.060**	1.573	0.061	**0.058**	**0.052**	**0.045**
	Energy	12	0.165	**0.145**	**0.142**	**0.148**	0.181	**0.125**	0.370	**0.153**	**0.163**	0.170	**0.159**
		24	0.292	0.299	0.308	0.302	0.301	0.317	1.273	0.309	0.316	0.309	0.323
		36	0.356	0.390	0.389	0.379	0.399	**0.337**	1.634	0.364	0.394	0.358	**0.349**
		48	0.485	**0.478**	**0.434**	0.495	0.495	**0.479**	1.258	**0.483**	**0.462**	**0.467**	0.490
	Environment	48	0.524	0.534	**0.522**	0.538	0.528	**0.510**	**0.482**	**0.521**	**0.498**	0.524	**0.472**
		96	0.549	0.554	**0.511**	0.564	0.560	**0.540**	**0.515**	**0.500**	**0.538**	**0.531**	**0.509**
		192	0.588	0.618	**0.535**	**0.570**	**0.562**	**0.568**	**0.574**	**0.551**	**0.535**	0.593	**0.523**
		336	0.572	**0.514**	**0.531**	**0.525**	**0.474**	**0.498**	**0.457**	**0.555**	**0.554**	**0.479**	**0.516**
	Public Health	12	1.668	**1.661**	**1.471**	1.740	**1.363**	**1.477**	**1.505**	**1.571**	**1.666**	**1.473**	**1.668**
		24	1.987	**1.953**	**1.795**	1.990	**1.945**	**1.854**	**1.693**	**1.852**	**1.921**	**1.850**	**1.787**
		36	1.920	1.977	2.004	**1.836**	2.123	1.975	**1.747**	**1.900**	2.041	1.920	1.961
		48	1.856	1.987	2.054	1.925	1.875	**1.775**	1.930	1.966	1.983	1.938	1.955
	Security	6	106.1	107.9	117.2	106.8	**105.7**	111.6	148.2	117.1	107.7	108.3	111.6
		8	110.7	112.1	**101.7**	112.5	110.9	112.5	137.2	**110.1**	113.4	**109.3**	**106.7**
		10	115.7	**115.2**	116.1	**115.2**	**111.7**	**111.3**	116.2	116.1	**112.2**	**111.7**	**113.0**
		12	117.8	**117.2**	**112.3**	**115.3**	**115.5**	**114.0**	118.3	**112.3**	**113.9**	**116.4**	**112.5**
	Social Good	6	0.838	0.888	**0.835**	0.853	**0.838**	0.863	4.334	**0.835**	0.874	0.905	0.842
		8	0.953	0.960	1.004	**0.949**	0.990	0.982	2.646	0.957	**0.938**	**0.947**	**0.909**
		10	1.058	**1.039**	1.058	**0.933**	1.097	**1.043**	1.123	**1.047**	1.062	**1.024**	**0.972**
		12	1.052	1.089	1.130	1.058	1.184	1.060	1.174	1.101	1.086	1.129	1.104
	Traffic	6	0.172	0.193	**0.170**	0.183	0.194	**0.168**	1.256	0.174	0.174	0.180	0.183
		8	0.206	**0.200**	**0.198**	**0.197**	0.219	**0.179**	1.718	0.211	**0.175**	**0.186**	**0.190**
		10	0.191	0.214	0.201	0.202	**0.184**	**0.176**	0.448	**0.187**	**0.189**	0.203	0.201
		12	0.239	0.266	**0.236**	0.251	0.267	**0.226**	0.414	**0.238**	0.246	**0.226**	**0.230**

Table 49: Multimodal fusion strategies with **Crossformer** (+ **GPT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Crossformer	Agriculture	6	0.088	0.132	0.146	0.115	**0.088**	0.152	0.210	0.159	0.184	0.213	0.166
		8	0.207	**0.194**	0.227	0.235	1.212	0.265	0.318	**0.171**	0.238	**0.167**	0.247
		10	0.252	0.301	**0.215**	0.376	**0.186**	0.300	0.470	**0.229**	**0.186**	0.255	0.260
		12	0.311	0.325	**0.225**	0.366	0.404	0.411	0.365	0.387	**0.301**	0.318	0.393
	Climate	6	1.039	1.054	1.083	1.065	1.057	1.042	1.051	1.062	1.063	**1.012**	1.119
		8	1.080	**1.070**	**1.047**	**1.066**	1.112	**1.072**	1.102	1.095	**1.074**	1.080	1.090
		10	1.088	1.117	1.090	**1.083**	**1.084**	**1.072**	1.099	**1.062**	**1.080**	1.099	1.113
		12	1.090	1.118	**1.082**	1.108	1.134	**1.076**	**1.086**	**1.083**	**1.085**	**1.086**	1.105
	Economy	6	0.468	**0.315**	**0.320**	**0.166**	**0.282**	0.508	0.499	**0.248**	**0.340**	**0.289**	**0.157**
		8	0.123	0.602	0.380	0.642	6.145	0.492	0.761	0.638	0.349	0.285	0.588
		10	0.122	0.700	0.382	0.673	0.554	0.866	0.686	0.693	0.424	0.445	0.365
		12	0.323	0.968	**0.299**	0.876	0.603	1.041	1.269	0.746	0.448	0.472	0.406
	Energy	12	0.145	**0.133**	**0.136**	**0.135**	0.169	0.165	**0.144**	**0.122**	**0.130**	**0.140**	0.155
		24	0.252	0.256	0.256	**0.239**	0.281	**0.225**	0.257	**0.234**	**0.243**	0.253	0.261
		36	0.345	0.357	**0.340**	**0.337**	**0.338**	0.354	**0.322**	**0.326**	0.345	**0.334**	**0.338**
		48	0.445	0.453	**0.429**	0.446	**0.419**	**0.430**	**0.383**	0.460	0.452	0.448	**0.427**
	Environment	48	0.492	0.499	**0.473**	0.500	**0.476**	**0.474**	**0.471**	0.500	**0.485**	**0.483**	**0.448**
		96	0.589	**0.536**	**0.529**	**0.529**	**0.584**	**0.492**	**0.557**	**0.561**	**0.521**	**0.535**	**0.513**
		192	0.551	0.585	0.571	0.574	**0.532**	0.587	0.600	**0.497**	0.572	0.578	**0.508**
		336	0.527	0.539	0.556	**0.494**	**0.499**	0.539	0.538	**0.522**	0.533	**0.527**	**0.511**
	Public Health	12	1.089	1.102	**1.080**	1.138	1.174	**1.053**	1.103	1.108	**1.082**	1.131	**1.044**
		24	1.305	1.320	1.352	1.375	1.394	1.415	1.440	1.424	1.328	**1.286**	1.333
		36	1.321	1.366	1.383	1.336	1.374	1.361	1.393	1.364	1.374	1.330	1.378
		48	1.440	1.479	**1.439**	1.447	1.456	1.452	1.476	1.528	1.473	1.470	1.497
	Security	6	118.2	122.5	120.1	120.2	120.9	118.4	124.9	119.6	121.7	119.7	**116.4**
		8	121.3	126.7	123.8	123.5	133.2	122.5	127.1	123.5	123.3	123.5	122.2
		10	125.3	126.2	**125.2**	125.5	**123.9**	128.6	125.6	**125.1**	126.2	125.6	**125.0**
		12	123.3	127.3	127.2	127.6	130.2	129.3	129.1	128.0	127.0	126.8	125.6
	Social Good	6	0.755	**0.743**	**0.743**	**0.745**	**0.732**	**0.745**	**0.727**	**0.744**	**0.734**	0.770	**0.744**
		8	0.813	0.827	**0.797**	**0.813**	1.868	**0.808**	0.817	0.814	**0.809**	0.843	0.842
		10	0.885	0.890	0.914	0.890	0.927	0.898	**0.874**	**0.871**	**0.863**	**0.878**	**0.872**
		12	0.941	0.942	**0.894**	0.957	0.970	**0.905**	**0.914**	0.961	**0.911**	**0.910**	**0.899**
	Traffic	6	0.215	**0.211**	0.219	**0.210**	0.229	**0.213**	0.225	**0.213**	0.223	**0.203**	0.217
		8	0.208	0.215	**0.205**	**0.208**	1.090	0.220	**0.202**	0.215	0.213	0.237	0.234
		10	0.211	0.227	0.225	0.228	0.226	0.224	0.228	0.220	0.220	0.219	**0.209**
		12	0.254	**0.247**	**0.250**	**0.244**	0.280	**0.244**	**0.252**	**0.251**	**0.242**	**0.248**	**0.246**

Table 50: Multimodal fusion strategies with **Reformer** (+ **GPT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Reformer	Agriculture	6	0.194	0.222	0.319	0.203	0.231	**0.182**	0.308	**0.132**	**0.142**	0.198	**0.183**
		8	0.254	0.383	0.323	**0.244**	**0.234**	0.375	0.406	0.325	**0.218**	0.391	**0.231**
		10	0.215	0.519	0.323	0.339	0.529	0.299	0.701	0.322	0.363	0.379	0.295
		12	0.467	0.490	0.518	**0.435**	0.644	0.588	**0.384**	0.551	**0.437**	0.479	**0.242**
	Climate	6	1.025	1.036	**1.012**	1.092	1.056	1.060	**0.967**	**1.010**	1.047	1.028	1.074
		8	1.066	1.070	**1.042**	**1.051**	**1.037**	1.101	**1.053**	**1.041**	1.070	1.088	1.079
		10	1.057	1.098	1.127	1.066	1.122	1.097	**0.913**	1.134	1.085	1.120	1.073
		12	1.075	1.109	**1.061**	**1.033**	1.103	1.103	**1.048**	**1.063**	1.095	**1.071**	1.108
	Economy	6	0.199	0.443	0.507	0.271	0.737	**0.151**	0.786	0.343	0.341	0.632	0.477
		8	0.337	0.720	0.342	**0.307**	0.802	0.814	0.993	0.337	0.409	0.372	**0.146**
		10	0.176	1.155	0.721	0.596	0.844	1.078	1.696	0.680	0.292	1.083	0.558
		12	0.144	1.249	1.342	0.748	1.324	1.318	0.854	1.341	0.972	0.728	0.483
	Energy	12	0.205	0.221	0.250	0.236	0.253	0.281	**0.203**	**0.135**	**0.138**	**0.177**	**0.190**
		24	0.423	**0.387**	**0.383**	**0.385**	**0.346**	0.458	**0.336**	**0.366**	**0.356**	0.438	**0.351**
		36	0.509	**0.475**	**0.493**	**0.484**	**0.437**	**0.490**	**0.443**	**0.387**	0.522	**0.461**	**0.419**
		48	0.574	**0.533**	**0.570**	**0.568**	0.596	**0.529**	**0.508**	**0.556**	**0.530**	**0.572**	**0.532**
	Environment	48	0.407	**0.404**	0.445	0.420	0.435	0.430	0.429	0.433	**0.401**	0.418	0.421
		96	0.447	**0.409**	0.461	**0.433**	**0.408**	0.458	0.450	**0.436**	**0.410**	**0.386**	**0.436**
		192	0.419	**0.411**	0.458	0.443	**0.411**	0.483	0.432	0.423	**0.390**	0.438	0.431
		336	0.473	**0.411**	**0.435**	**0.437**	**0.399**	**0.433**	**0.472**	**0.411**	**0.418**	**0.383**	**0.413**
	Public Health	12	1.157	**1.111**	**1.142**	**1.148**	**1.137**	**1.096**	**1.085**	**1.131**	**1.048**	**1.106**	**1.071**
		24	1.231	1.417	1.320	1.293	1.445	1.395	1.500	1.335	1.339	1.350	1.288
		36	1.307	1.331	**1.288**	1.492	1.407	**1.292**	1.409	**1.289**	**1.285**	1.366	1.365
		48	1.356	1.431	1.416	1.430	1.609	1.404	1.475	**1.267**	**1.331**	1.406	**1.330**
	Security	6	118.3	120.0	123.7	124.1	118.5	118.6	122.4	123.7	125.2	125.4	123.6
		8	121.6	**121.1**	121.8	124.5	122.7	123.8	125.0	121.8	123.1	124.0	123.4
		10	126.2	**125.7**	**124.5**	**125.4**	129.0	**122.6**	126.7	**124.5**	**125.0**	**125.5**	**125.3**
		12	128.0	**122.1**	**125.6**	**125.9**	**126.7**	**124.7**	**126.0**	**125.6**	**126.1**	**125.1**	**125.9**
	Social Good	6	0.802	0.819	0.836	**0.775**	0.874	0.823	**0.771**	0.836	0.861	**0.800**	**0.787**
		8	0.846	0.918	0.911	0.852	0.909	0.893	0.849	0.900	0.862	0.887	0.865
		10	0.948	**0.929**	0.968	**0.914**	1.021	1.017	**0.903**	0.967	0.968	**0.905**	0.989
		12	1.023	1.097	1.052	**0.963**	**1.016**	**1.023**	1.029	**0.921**	**0.966**	**1.013**	**0.973**
	Traffic	6	0.208	0.268	0.229	0.255	0.250	0.303	0.259	0.229	0.233	0.257	0.242
		8	0.224	0.237	0.225	0.225	0.226	0.279	0.230	0.225	0.229	0.237	0.253
		10	0.261	0.273	0.309	0.269	**0.242**	0.297	**0.225**	0.298	**0.235**	0.278	**0.246**
		12	0.245	0.253	0.256	0.275	0.252	0.280	0.249	0.259	0.266	0.274	0.252

Table 51: Multimodal fusion strategies with **Transformer** (+ **GPT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Transformer	Agriculture	6	0.133	**0.119**	0.177	0.137	0.159	**0.119**	0.217	0.188	0.165	0.140	0.153
		8	0.147	0.334	**0.143**	0.243	0.210	0.174	0.433	0.163	0.161	0.211	0.182
		10	0.177	0.524	0.282	0.273	**0.133**	0.210	0.666	0.203	**0.172**	0.178	**0.158**
		12	0.247	0.312	0.254	0.325	**0.174**	0.286	0.485	0.264	**0.240**	0.254	**0.244**
	Climate	6	0.985	1.032	0.989	1.022	**0.875**	0.990	**0.983**	0.989	1.024	1.055	**0.984**
		8	1.058	**1.055**	**0.989**	**1.055**	1.086	1.091	**0.990**	**0.989**	**1.032**	**1.054**	**1.053**
		10	1.068	1.091	**1.056**	1.072	**1.066**	**1.003**	**1.016**	**1.056**	**1.021**	1.083	1.085
		12	1.102	**0.991**	**1.029**	**1.094**	1.122	**1.078**	**1.073**	**1.029**	**1.056**	**1.063**	**1.018**
	Economy	6	0.267	**0.245**	**0.059**	0.287	**0.239**	**0.267**	0.610	**0.143**	**0.061**	**0.092**	0.275
		8	0.287	0.566	**0.283**	**0.154**	**0.282**	0.320	0.571	0.390	0.506	0.515	0.327
		10	0.258	1.063	0.315	0.676	**0.069**	**0.110**	1.294	0.417	0.262	**0.250**	**0.247**
		12	0.362	1.067	0.420	**0.113**	**0.050**	0.544	0.706	**0.052**	**0.237**	**0.279**	**0.044**
	Energy	12	0.122	**0.111**	**0.091**	0.130	**0.109**	0.137	**0.101**	**0.100**	**0.105**	**0.081**	**0.121**
		24	0.289	0.295	**0.179**	**0.247**	**0.225**	**0.149**	0.318	**0.237**	**0.240**	**0.228**	**0.209**
		36	0.261	0.414	0.326	0.350	0.380	0.272	0.310	0.319	0.318	0.293	0.373
		48	0.450	**0.445**	**0.348**	0.525	**0.390**	**0.409**	**0.390**	**0.352**	0.480	**0.367**	**0.402**
	Environment	48	0.429	0.461	**0.428**	**0.426**	**0.412**	**0.405**	0.436	**0.405**	**0.420**	**0.413**	**0.419**
		96	0.462	0.482	**0.450**	**0.449**	**0.445**	**0.449**	0.467	**0.447**	**0.432**	**0.423**	**0.439**
		192	0.450	0.535	0.474	**0.446**	0.454	**0.437**	0.511	0.474	**0.445**	**0.427**	0.466
		336	0.451	0.485	0.459	**0.439**	0.465	**0.445**	0.452	**0.424**	**0.436**	**0.421**	0.469
	Public Health	12	1.124	1.137	1.201	**1.121**	**1.026**	**1.037**	**1.054**	**1.102**	**0.859**	**1.104**	**1.021**
		24	1.370	**1.278**	**1.263**	1.388	**1.121**	**1.220**	**1.331**	**1.263**	**1.256**	**1.340**	**1.286**
		36	1.317	1.330	**1.295**	**1.308**	1.438	**1.284**	1.351	**1.295**	**1.293**	**1.258**	1.330
		48	1.389	1.450	**1.316**	1.479	1.420	**1.378**	1.443	1.415	1.438	**1.309**	1.482
	Security	6	124.0	127.2	126.3	**123.0**	**122.4**	127.0	**123.1**	126.3	125.1	124.9	125.9
		8	124.8	130.8	127.0	128.7	125.9	129.5	127.9	127.1	128.8	128.6	128.1
		10	129.7	131.4	130.6	131.5	**125.0**	**128.5**	**129.5**	**128.6**	132.8	**129.7**	**129.0**
		12	130.3	**117.9**	131.2	**128.6**	**127.3**	132.0	131.5	131.2	130.4	130.6	**127.1**
	Social Good	6	0.731	0.784	0.774	0.763	0.787	**0.718**	0.769	0.758	0.792	0.744	0.740
		8	0.763	0.792	0.894	0.828	0.884	0.896	0.807	0.889	0.836	0.826	0.791
		10	0.828	**0.788**	0.925	0.845	0.965	0.918	**0.806**	0.952	0.913	0.884	0.864
		12	0.832	0.854	0.903	**0.828**	0.946	0.915	0.926	0.903	0.934	0.907	0.921
	Traffic	6	0.167	0.172	**0.157**	**0.162**	0.175	0.170	**0.153**	**0.157**	**0.156**	0.172	**0.153**
		8	0.159	**0.156**	0.175	0.174	0.192	0.175	0.175	0.175	**0.158**	0.164	0.187
		10	0.181	0.217	0.182	**0.171**	0.202	0.206	0.182	0.181	0.183	**0.178**	0.194
		12	0.214	0.243	**0.207**	**0.212**	0.246	0.239	**0.206**	**0.207**	**0.211**	**0.199**	0.221

Table 52: Multimodal fusion strategies with **TSMixer** (+ **GPT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
TSMixer	Agriculture	6	0.083	0.105	0.142	0.117	0.154	0.142	0.111	0.103	0.158	0.113	0.092
		8	0.125	0.220	0.217	0.180	0.278	0.182	0.165	0.185	0.217	0.174	0.136
		10	0.428	0.515	1.135	**0.390**	**0.380**	1.077	**0.240**	**0.323**	1.309	0.619	**0.204**
		12	0.834	1.352	1.080	1.080	1.496	**0.458**	**0.386**	**0.397**	1.398	1.012	**0.281**
	Climate	6	1.054	1.061	1.061	1.080	1.085	1.083	1.101	1.065	**1.054**	1.069	1.070
		8	1.088	**1.073**	1.097	**1.084**	1.100	**1.085**	1.096	1.111	1.108	1.091	1.095
		10	1.105	1.116	1.177	1.143	1.106	1.106	**1.097**	1.115	1.123	1.124	1.113
		12	1.106	1.168	1.132	1.153	1.148	**1.106**	1.112	1.141	1.136	1.132	1.106
	Economy	6	0.074	0.112	0.099	0.108	**0.065**	0.091	0.082	0.096	**0.067**	0.075	**0.050**
		8	0.063	0.411	0.405	0.158	0.622	0.245	0.154	0.201	0.219	0.117	0.080
		10	0.109	1.445	1.748	0.709	**0.107**	1.900	0.136	0.373	2.045	1.239	0.155
		12	0.874	2.445	2.292	2.204	2.545	**0.603**	**0.523**	1.225	2.047	2.154	**0.208**
	Energy	12	0.142	0.161	0.164	**0.140**	0.157	0.149	0.146	0.162	0.152	0.163	**0.115**
		24	0.286	**0.274**	**0.278**	0.303	**0.255**	**0.237**	**0.282**	**0.238**	**0.272**	**0.261**	**0.264**
		36	0.360	**0.347**	0.362	0.360	0.369	**0.359**	**0.341**	**0.315**	**0.356**	**0.347**	0.360
		48	0.456	**0.436**	0.504	0.470	**0.449**	0.470	**0.418**	**0.416**	0.488	**0.446**	**0.445**
	Environment	48	0.542	**0.505**	**0.509**	**0.487**	**0.461**	**0.479**	**0.493**	**0.525**	**0.438**	**0.488**	**0.502**
		96	0.606	**0.495**	**0.518**	**0.489**	**0.515**	**0.449**	**0.549**	**0.592**	**0.478**	**0.474**	**0.556**
		192	0.660	**0.645**	**0.537**	**0.500**	**0.607**	**0.583**	**0.531**	**0.641**	**0.504**	**0.498**	**0.619**
		336	0.581	**0.576**	**0.580**	**0.555**	**0.561**	**0.559**	**0.530**	0.587	**0.534**	**0.560**	**0.558**
	Public Health	12	1.150	**0.991**	**1.099**	**1.137**	1.160	**1.102**	**1.065**	**1.090**	1.195	**1.095**	**1.086**
		24	1.393	1.551	1.407	1.415	**1.372**	1.413	1.462	**1.308**	1.480	1.452	1.444
		36	1.500	1.721	1.587	**1.472**	1.536	1.562	1.503	**1.362**	1.505	1.525	**1.466**
		48	1.687	**1.608**	1.738	**1.627**	**1.618**	1.742	**1.599**	**1.586**	1.700	**1.635**	**1.625**
	Security	6	128.0	**127.8**	**128.0**	128.9	**125.4**	**127.4**	129.6	**126.7**	128.6	**127.6**	**124.4**
		8	127.4	**124.2**	128.3	128.8	**125.6**	**119.5**	133.6	128.0	**126.0**	127.5	**126.4**
		10	128.2	131.5	130.5	132.6	128.6	128.5	128.7	134.2	128.8	129.7	128.2
		12	130.7	133.2	133.3	133.5	132.4	**127.2**	**130.7**	133.0	132.3	132.5	131.3
	Social Good	6	0.778	0.812	**0.764**	0.827	0.783	**0.756**	**0.751**	0.805	0.826	**0.774**	**0.742**
		8	0.862	0.939	1.034	0.940	**0.791**	0.929	0.884	0.883	0.900	0.876	**0.819**
		10	0.867	0.945	1.103	0.935	0.881	0.924	0.955	0.993	1.112	1.045	**0.832**
		12	0.902	0.977	1.134	0.969	0.973	0.939	**0.890**	1.025	1.064	1.100	**0.873**
	Traffic	6	0.203	0.226	0.230	0.205	0.221	0.222	0.233	0.221	0.237	0.231	**0.190**
		8	0.216	0.248	0.228	0.234	0.276	0.251	0.255	0.287	0.249	0.228	**0.185**
		10	0.229	0.326	0.424	0.320	0.238	0.450	0.238	0.269	0.388	0.255	**0.207**
		12	0.303	0.527	0.544	0.396	0.512	**0.283**	**0.280**	0.362	0.477	0.506	**0.266**

Table 53: Multimodal fusion strategies with **Informer** (+ **GPT**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Informer	Agriculture	6	0.212	0.373	0.283	0.319	0.308	**0.194**	0.228	**0.189**	0.395	0.293	**0.198**
		8	0.315	0.415	**0.251**	0.346	**0.204**	**0.280**	0.322	**0.193**	0.392	0.352	0.348
		10	0.417	**0.236**	**0.386**	0.440	0.578	**0.353**	**0.381**	**0.321**	**0.352**	**0.311**	**0.403**
		12	0.565	**0.405**	0.621	0.593	**0.320**	0.648	0.597	0.581	**0.436**	**0.365**	**0.453**
	Climate	6	1.070	**1.066**	1.111	**1.058**	**1.019**	**1.034**	**1.022**	**1.046**	**1.031**	**1.061**	**1.040**
		8	1.081	**1.065**	1.083	**1.073**	**0.916**	1.087	**1.073**	**1.047**	**1.073**	**1.049**	1.108
		10	1.060	1.074	1.081	1.067	**0.988**	1.072	1.060	1.074	1.106	1.075	1.104
		12	1.050	1.086	1.097	1.073	**0.916**	**1.036**	1.067	1.095	1.085	1.095	1.096
	Economy	6	0.497	0.765	**0.272**	0.724	0.597	**0.372**	0.737	**0.406**	0.532	**0.368**	0.691
		8	0.529	1.003	0.596	0.848	**0.337**	1.153	1.026	0.541	**0.461**	**0.432**	**0.467**
		10	0.761	1.011	**0.709**	1.001	1.135	**0.231**	0.804	**0.374**	0.833	**0.624**	1.208
		12	1.113	1.216	**0.595**	**1.036**	**0.803**	1.501	1.141	**0.062**	**0.777**	**0.914**	**0.768**
	Energy	12	0.137	0.154	0.212	0.169	0.185	0.172	0.171	0.217	0.155	0.189	0.155
		24	0.316	**0.296**	**0.302**	**0.316**	**0.291**	0.340	0.338	**0.249**	**0.299**	**0.308**	**0.300**
		36	0.411	**0.372**	0.444	**0.375**	0.430	**0.374**	**0.355**	0.430	**0.317**	**0.387**	**0.367**
		48	0.483	**0.464**	0.488	0.546	**0.466**	0.495	**0.442**	0.498	**0.478**	0.491	0.528
	Environment	48	0.424	**0.422**	0.428	0.438	0.440	**0.415**	0.442	0.447	0.437	0.440	**0.409**
		96	0.437	**0.437**	0.448	0.446	0.446	**0.437**	0.443	**0.408**	**0.412**	**0.405**	**0.416**
		192	0.449	0.508	**0.399**	0.463	**0.427**	0.468	**0.419**	**0.398**	**0.428**	**0.414**	**0.410**
		336	0.464	**0.464**	0.473	0.469	**0.435**	0.466	0.485	**0.443**	**0.410**	**0.401**	0.468
	Public Health	12	1.236	**1.054**	**1.075**	**1.066**	**1.011**	**0.997**	**1.056**	**1.016**	**1.084**	**1.002**	**1.131**
		24	1.373	**1.175**	1.383	1.376	**1.267**	**1.321**	**1.286**	**1.339**	**1.255**	1.426	**1.252**
		36	1.540	**1.349**	**1.449**	**1.442**	**1.200**	**1.431**	**1.473**	**1.434**	**1.441**	1.544	**1.406**
		48	1.643	**1.551**	1.659	**1.637**	**1.310**	**1.596**	**1.569**	**1.524**	**1.625**	1.670	**1.633**
	Security	6	124.8	127.2	126.3	128.0	**124.0**	127.6	126.3	**124.3**	126.4	127.4	127.6
		8	126.7	130.4	128.9	129.9	**126.4**	127.2	**126.7**	**125.5**	**125.4**	**126.3**	**125.6**
		10	127.8	**126.6**	**126.7**	**126.1**	130.8	130.0	128.3	129.2	130.8	131.2	129.1
		12	131.1	132.6	131.2	131.8	**128.0**	131.9	**130.5**	132.1	**130.2**	**128.0**	131.3
	Social Good	6	0.726	**0.706**	0.729	**0.723**	0.779	0.750	0.733	0.747	0.730	0.726	0.753
		8	0.787	0.803	**0.781**	0.808	0.867	0.816	0.825	0.817	0.792	0.795	**0.778**
		10	0.825	0.847	0.833	0.866	**0.820**	0.878	0.835	0.909	0.849	**0.815**	0.873
		12	0.833	0.879	**0.830**	0.858	0.929	0.877	0.858	0.939	0.868	0.918	0.872
	Traffic	6	0.164	0.172	0.173	**0.149**	**0.158**	**0.163**	**0.150**	0.178	**0.152**	**0.150**	0.170
		8	0.161	0.191	**0.158**	0.169	0.187	0.163	0.163	0.181	0.169	0.162	0.167
		10	0.198	**0.187**	**0.195**	**0.182**	0.205	**0.181**	**0.179**	**0.177**	**0.174**	**0.173**	**0.182**
		12	0.225	0.228	**0.207**	**0.220**	**0.203**	**0.215**	**0.219**	**0.211**	**0.205**	**0.203**	**0.222**

Text Model: Llama-3. The following tables report the Llama-3-based results, where Llama-3 serves as a stronger large language model encoder compared to BERT and GPT-2. Despite Llama-3's substantially larger parameter count and more powerful representations, we observe that naive fusion still under-performs the unimodal baseline in many configurations, while CFA continues to deliver consistent improvements across backbones and datasets.

Table 54: Multimodal fusion strategies with **Nonstationary Transformer** (+ **LLAMA3**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Nonstationary Transformer	Agriculture	6	0.049	0.050	0.051	0.054	0.060	0.055	1.435	0.052	0.053	0.051	0.054
		8	0.071	0.072	0.072	**0.070**	0.074	0.071	0.501	**0.070**	0.072	0.072	**0.069**
		10	0.092	0.096	**0.091**	0.094	0.095	0.095	0.333	**0.092**	**0.091**	**0.090**	**0.090**
		12	0.116	0.118	0.120	0.118	0.120	0.119	0.359	**0.116**	**0.116**	0.118	**0.115**
	Climate	6	1.239	1.297	1.254	**1.195**	**1.067**	1.242	**1.132**	1.243	1.258	1.252	**0.998**
		8	1.244	1.314	1.292	**1.239**	**1.139**	**1.210**	**1.194**	**1.141**	**1.201**	**1.209**	1.297
		10	1.222	1.291	1.256	1.315	1.294	**1.192**	**1.061**	1.249	1.280	1.254	1.243
		12	1.273	1.299	**1.202**	**1.240**	**1.242**	**1.179**	**1.054**	**1.245**	**1.229**	**1.207**	**1.214**
	Economy	6	0.017	0.017	**0.017**	0.019	0.017	**0.016**	9.652	0.017	0.019	**0.016**	0.018
		8	0.018	0.019	0.019	0.019	0.021	**0.018**	6.299	**0.018**	0.019	**0.017**	0.020
		10	0.020	0.021	**0.019**	0.020	**0.019**	**0.020**	0.895	0.021	**0.019**	**0.020**	**0.019**
		12	0.021	**0.021**	**0.020**	0.024	**0.020**	0.022	0.882	**0.020**	**0.020**	**0.020**	**0.021**
	Energy	12	0.104	**0.096**	**0.093**	0.106	**0.090**	0.109	0.187	**0.103**	0.104	**0.083**	**0.092**
		24	0.190	0.244	0.197	0.209	**0.174**	0.199	0.663	0.197	0.209	0.192	0.206
		36	0.293	0.308	**0.282**	0.303	**0.233**	**0.292**	1.211	**0.281**	0.329	**0.289**	**0.244**
		48	0.425	0.451	0.439	**0.411**	**0.392**	0.435	0.761	**0.397**	**0.343**	**0.312**	**0.417**
	Environment	48	0.433	0.434	0.441	**0.432**	0.449	0.438	0.486	0.436	**0.433**	**0.429**	**0.430**
		96	0.440	0.466	0.467	0.452	0.449	**0.433**	0.470	0.443	0.456	0.449	0.450
		192	0.434	0.477	0.442	0.479	0.449	0.456	0.511	**0.417**	0.457	**0.422**	**0.434**
		336	0.431	0.502	**0.431**	0.450	0.438	0.449	0.463	0.444	0.438	0.438	0.435
	Public Health	12	0.781	0.873	0.782	1.050	0.927	0.904	1.104	0.887	0.817	**0.748**	0.807
		24	1.165	1.177	**1.104**	1.329	1.299	**1.151**	1.647	1.245	**0.913**	**1.067**	**1.091**
		36	1.214	1.389	**1.207**	1.215	1.400	1.300	1.750	1.371	1.244	**1.192**	1.244
		48	1.829	1.995	**1.294**	**1.431**	**1.796**	**1.358**	**1.502**	**1.482**	**1.392**	**1.337**	**1.287**
	Security	6	103.7	**101.7**	**101.3**	108.6	**101.3**	106.1	125.5	**101.6**	**100.7**	**102.3**	**101.8**
		8	105.2	105.5	111.3	107.4	105.7	**101.2**	125.4	**105.1**	**105.0**	**103.8**	**104.4**
		10	108.9	**107.9**	111.3	**107.9**	**107.8**	**107.1**	120.0	**107.8**	**107.7**	**107.2**	**107.5**
		12	109.1	109.5	110.7	109.5	109.6	**107.4**	119.9	109.8	109.5	109.5	**109.1**
	Social Good	6	0.828	**0.786**	**0.758**	**0.731**	**0.757**	**0.770**	4.342	**0.769**	**0.753**	**0.769**	**0.785**
		8	0.900	0.972	**0.851**	**0.874**	1.035	**0.879**	2.818	**0.897**	**0.893**	**0.868**	0.938
		10	1.031	**0.971**	**0.990**	**0.958**	1.099	**1.013**	1.109	**0.985**	**0.977**	**1.012**	**0.959**
		12	0.983	1.079	**0.933**	0.987	1.083	1.104	1.073	1.050	1.055	1.039	1.040
	Traffic	6	0.178	0.183	0.185	**0.178**	0.184	**0.170**	0.405	0.181	**0.177**	**0.170**	0.179
		8	0.185	0.190	**0.182**	0.188	0.194	0.192	0.319	0.187	**0.176**	**0.183**	**0.185**
		10	0.186	0.204	**0.182**	0.193	0.193	**0.181**	0.208	0.196	0.188	**0.184**	**0.185**
		12	0.234	0.246	0.256	0.261	0.247	0.253	0.265	0.253	0.258	0.246	0.246

Table 55: Multimodal fusion strategies with **PatchTST** (+ **LLAMA3**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
PatchTST	Agriculture	6	0.060	**0.060**	**0.059**	**0.057**	**0.060**	0.061	1.363	**0.056**	**0.058**	**0.059**	0.061
		8	0.077	0.078	0.080	**0.075**	0.078	0.078	0.719	0.080	0.080	0.079	0.078
		10	0.100	0.100	0.102	**0.100**	0.100	0.101	0.304	0.102	0.102	0.101	0.101
		12	0.130	**0.129**	0.131	**0.129**	**0.129**	0.130	0.392	0.131	0.131	0.130	**0.129**
	Climate	6	1.257	**1.229**	**1.235**	**1.232**	**1.229**	**1.251**	**1.220**	**1.235**	**1.241**	1.267	**1.240**
		8	1.248	1.252	**1.221**	1.251	1.252	1.266	1.317	**1.221**	1.257	**1.242**	**1.244**
		10	1.273	1.278	**1.257**	1.284	1.278	**1.265**	**1.109**	**1.257**	**1.250**	**1.260**	**1.262**
		12	1.241	1.251	1.250	1.263	1.251	1.257	**1.100**	1.250	1.263	**1.240**	1.249
	Economy	6	0.017	**0.016**	0.017	0.018	**0.016**	0.017	13.809	0.017	**0.016**	0.017	0.017
		8	0.017	**0.017**	0.017	0.019	**0.017**	0.018	6.810	0.017	0.017	**0.016**	0.017
		10	0.017	**0.016**	**0.017**	0.020	**0.016**	0.018	1.752	**0.017**	0.018	**0.017**	**0.017**
		12	0.018	**0.017**	0.018	0.021	**0.017**	0.018	1.664	0.018	0.018	**0.017**	**0.017**
	Energy	12	0.109	**0.106**	0.111	0.125	**0.106**	**0.108**	0.260	0.111	0.112	0.111	**0.108**
		24	0.211	**0.208**	0.217	0.242	**0.208**	0.219	0.730	0.222	0.220	0.219	0.212
		36	0.307	0.318	**0.304**	0.323	0.318	**0.301**	1.214	0.310	0.310	**0.286**	0.312
		48	0.416	**0.415**	**0.393**	0.446	**0.415**	**0.416**	0.687	**0.394**	**0.404**	0.419	0.423
	Environment	48	0.462	0.463	**0.458**	0.506	0.463	**0.451**	0.489	**0.455**	**0.454**	**0.458**	**0.453**
		96	0.508	**0.501**	**0.461**	**0.472**	**0.501**	**0.455**	0.514	**0.455**	**0.456**	**0.466**	**0.452**
		192	0.540	**0.539**	**0.450**	**0.503**	**0.539**	**0.447**	0.591	**0.458**	**0.439**	**0.465**	**0.436**
		336	0.511	**0.508**	**0.441**	0.524	**0.508**	**0.453**	**0.482**	**0.446**	**0.441**	**0.442**	**0.426**
	Public Health	12	0.926	0.947	0.937	**0.883**	0.947	0.966	**0.909**	0.949	1.007	0.945	**0.890**
		24	1.403	**1.283**	1.423	**1.191**	**1.283**	**1.298**	1.495	**1.264**	1.418	**1.287**	**1.312**
		36	1.602	1.614	1.620	**1.391**	1.614	1.628	2.030	1.621	1.631	1.619	1.662
		48	1.721	1.743	1.760	**1.547**	1.743	1.752	**1.602**	1.761	1.763	1.740	1.785
	Security	6	105.0	**104.3**	**102.8**	105.8	**104.3**	**102.6**	141.8	**103.0**	**104.2**	**103.6**	**103.7**
		8	107.8	110.1	**105.7**	**104.4**	110.1	**106.1**	141.6	**105.7**	**106.4**	**107.6**	**107.1**
		10	110.0	111.5	**108.6**	113.1	111.5	**109.2**	119.1	**109.0**	110.6	**109.8**	**108.1**
		12	111.1	**111.0**	**110.7**	111.2	**111.0**	**110.3**	118.9	111.3	111.5	**111.0**	113.1
	Social Good	6	0.790	0.794	0.795	**0.774**	0.794	0.792	4.279	0.795	0.808	**0.787**	0.813
		8	0.914	**0.907**	**0.891**	**0.845**	**0.907**	**0.893**	2.796	**0.891**	**0.912**	**0.869**	0.933
		10	1.022	1.041	**1.012**	**0.966**	1.041	1.023	1.083	**1.012**	**0.966**	1.027	1.043
		12	1.119	**1.075**	**1.052**	**1.045**	**1.095**	**1.087**	**1.057**	**1.014**	**1.099**	**1.112**	**1.088**
	Traffic	6	0.170	0.173	0.178	0.191	0.173	0.181	0.423	0.177	0.175	**0.169**	0.177
		8	0.183	**0.180**	0.183	0.189	**0.180**	0.190	0.294	0.184	0.183	0.189	0.186
		10	0.196	**0.195**	0.199	0.202	**0.195**	0.196	0.214	**0.196**	**0.189**	**0.184**	**0.190**
		12	0.242	0.243	**0.230**	0.249	0.243	0.253	**0.242**	**0.242**	**0.237**	**0.229**	0.245

Table 56: Multimodal fusion strategies with **iTransformer** (+ **LLAMA3**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
iTransformer	Agriculture	6	0.060	**0.059**	0.060	**0.058**	0.064	**0.059**	1.286	0.060	0.060	0.060	0.060
		8	0.077	**0.077**	0.080	**0.074**	0.078	0.079	0.961	0.080	0.079	0.080	0.078
		10	0.096	0.100	0.102	0.098	0.101	0.100	0.187	0.101	0.102	0.101	0.099
		12	0.129	**0.128**	0.131	**0.126**	0.131	0.131	0.309	0.130	0.130	0.129	**0.128**
	Climate	6	1.116	**1.116**	**1.113**	1.124	1.131	1.160	1.321	**1.113**	1.117	1.145	1.125
		8	1.179	**1.173**	1.197	1.234	**1.078**	1.181	1.334	1.197	**1.179**	1.192	1.196
		10	1.233	**1.212**	**1.197**	1.240	**1.174**	**1.182**	**1.069**	**1.197**	**1.215**	**1.188**	**1.189**
		12	1.181	**1.180**	1.183	1.200	1.192	1.198	**1.055**	1.182	1.185	1.184	1.188
	Economy	6	0.015	0.015	0.015	0.019	**0.015**	0.015	10.938	**0.015**	**0.015**	**0.015**	**0.015**
		8	0.015	**0.015**	0.015	0.016	0.015	**0.015**	9.176	0.015	**0.015**	0.016	0.015
		10	0.016	0.016	0.016	0.016	**0.015**	0.016	1.473	0.016	**0.015**	**0.016**	**0.016**
		12	0.016	**0.016**	0.016	0.017	**0.016**	**0.016**	1.125	0.016	0.016	**0.016**	**0.016**
	Energy	12	0.112	**0.108**	**0.099**	**0.106**	**0.096**	0.117	0.248	**0.106**	**0.108**	0.114	0.114
		24	0.232	**0.215**	**0.207**	0.237	**0.177**	**0.208**	0.837	**0.210**	**0.225**	**0.220**	**0.218**
		36	0.286	0.323	0.298	0.326	**0.273**	0.294	1.181	0.291	0.302	**0.284**	**0.286**
		48	0.406	**0.389**	**0.376**	0.418	**0.384**	0.414	0.671	**0.376**	**0.379**	0.407	**0.398**
	Environment	48	0.407	0.420	0.415	0.429	**0.404**	0.418	0.495	0.423	0.421	0.411	0.416
		96	0.417	0.420	0.431	0.461	**0.409**	0.430	0.547	0.449	0.427	0.422	0.436
		192	0.425	0.440	0.449	0.454	0.430	0.429	0.492	0.443	0.437	0.442	0.445
		336	0.421	0.422	0.432	0.443	0.421	0.427	0.423	0.426	0.427	**0.414**	0.433
	Public Health	12	0.998	1.005	**0.892**	**0.927**	**0.931**	**0.988**	**0.997**	**0.949**	**0.956**	1.014	**0.991**
		24	1.447	1.458	1.483	**1.167**	1.468	1.447	1.451	1.479	1.516	1.448	1.448
		36	1.629	1.682	1.630	**1.333**	1.677	1.643	1.751	**1.628**	1.641	**1.624**	1.659
		48	1.749	1.759	1.754	**1.481**	1.789	**1.747**	**1.689**	1.754	1.751	**1.743**	1.777
	Security	6	104.9	**103.2**	**102.3**	113.6	**103.6**	**103.1**	141.9	**102.1**	**104.6**	**102.7**	**104.4**
		8	109.0	**107.6**	**105.3**	113.8	**105.9**	**106.0**	138.4	**105.1**	**106.8**	**107.7**	**106.1**
		10	111.8	**110.1**	**107.8**	116.9	**110.2**	**108.7**	121.6	**106.7**	**110.4**	**108.7**	**111.4**
		12	114.5	**110.1**	**110.0**	114.7	**110.9**	**110.4**	118.3	**109.9**	**110.5**	**110.8**	**111.6**
	Social Good	6	0.836	**0.830**	**0.820**	**0.784**	0.845	0.838	4.297	**0.820**	**0.822**	**0.822**	**0.827**
		8	0.958	0.967	**0.949**	**0.929**	**0.932**	**0.940**	2.814	**0.949**	**0.930**	**0.905**	0.964
		10	1.057	1.060	**1.043**	**1.053**	1.072	**1.047**	1.105	**1.043**	1.073	**0.993**	1.066
		12	1.138	1.165	**1.130**	1.164	**1.098**	**1.127**	**1.136**	**1.109**	1.149	1.157	**1.099**
	Traffic	6	0.177	**0.176**	0.181	0.186	**0.173**	0.186	0.444	0.181	**0.173**	0.179	**0.174**
		8	0.184	0.194	0.196	0.197	0.201	0.188	0.376	0.191	**0.179**	**0.179**	**0.183**
		10	0.196	0.198	**0.187**	0.199	0.203	0.197	0.212	**0.187**	**0.180**	**0.178**	0.197
		12	0.245	0.252	0.246	0.266	0.251	**0.233**	**0.243**	0.248	**0.240**	**0.229**	0.247

Table 57: Multimodal fusion strategies with **Koopa** (+ **LLAMA3**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	CFA
Koopa	Agriculture	6	0.058	0.068	0.065	0.065	1.282	1.889	1.889	0.058	0.069	0.059	**0.057**
		8	0.077	0.100	0.092	0.092	0.141	0.095	0.095	0.078	0.121	0.078	**0.076**
		10	0.099	**0.093**	**0.091**	**0.091**	1.348	0.508	0.508	0.100	0.135	**0.097**	0.099
		12	0.128	0.137	0.133	0.133	0.981	1.731	1.731	0.129	0.134	0.137	**0.128**
	Climate	6	1.250	14.014	1.277	1.277	14.658	1.264	1.264	1.292	**1.104**	**1.250**	**1.248**
		8	1.290	1.492	**1.281**	**1.281**	**1.207**	**1.112**	**1.112**	1.292	**1.074**	**1.254**	**1.263**
		10	1.247	1.424	1.277	1.277	**1.215**	**1.087**	**1.087**	1.259	**1.112**	1.257	**1.246**
		12	1.236	1.250	1.275	1.275	**1.178**	1.370	1.370	1.256	**1.081**	1.262	**1.232**
	Economy	6	0.017	0.028	0.029	0.029	14.050	12.126	12.126	0.029	0.038	0.035	**0.017**
		8	0.018	0.020	0.021	0.021	0.771	0.302	0.302	0.019	0.095	0.019	**0.017**
		10	0.018	0.029	0.034	0.034	2.712	2.162	2.162	0.028	0.102	0.021	**0.018**
		12	0.018	0.031	0.025	0.025	15.161	8.553	8.553	0.025	0.053	0.032	**0.017**
	Energy	12	0.107	10830.7	0.124	0.124	448.7	0.147	0.147	0.118	**0.106**	0.116	**0.107**
		24	0.214	1093.2	0.238	0.238	2.765	0.386	0.386	0.234	0.228	0.221	**0.204**
		36	0.298	**0.281**	0.329	0.329	0.611	0.611	0.611	0.315	0.323	0.310	**0.296**
		48	0.406	0.497	0.413	0.413	2.152	0.904	0.904	0.424	**0.402**	0.434	**0.405**
	Environment	48	0.484	1961952000.0	**0.478**	**0.478**	405995840.0	**0.453**	**0.453**	0.488	**0.440**	**0.441**	0.484
		96	0.528	2833084928.0	**0.462**	**0.462**	960262208.0	**0.466**	**0.466**	0.543	**0.454**	**0.469**	0.533
		192	0.567	6696846336.0	**0.542**	**0.542**	45984964.0	**0.499**	**0.499**	0.572	**0.506**	**0.539**	**0.564**
		336	0.531	13381508096.0	0.533	0.533	138449984.0	**0.495**	**0.495**	0.534	**0.507**	**0.529**	**0.527**
	Public Health	12	1.045	5541.8	**0.961**	**0.961**	234.6	**1.026**	**1.026**	1.239	**1.011**	**0.964**	**1.027**
		24	1.396	**1.158**	**1.224**	**1.224**	1.838	**1.307**	**1.307**	1.517	1.779	**1.177**	1.400
		36	1.629	**1.319**	**1.347**	**1.347**	2.208	**1.528**	**1.528**	1.798	**1.457**	**1.306**	**1.618**
		48	1.732	2.800	**1.446**	**1.446**	**1.726**	1.803	1.803	1.869	1.760	**1.414**	**1.714**
	Security	6	104.7	105.4	**102.3**	**102.3**	135.7	144.0	144.0	**104.3**	111.3	**103.7**	**104.7**
		8	108.6	108.7	111.3	111.3	108.8	**107.4**	**107.4**	113.9	114.7	110.5	**108.5**
		10	109.1	**107.3**	**107.9**	**107.9**	117.8	118.1	118.1	110.8	117.9	109.1	**108.6**
		12	111.4	**110.3**	**109.8**	**109.8**	157.0	144.3	144.3	114.5	117.3	**108.3**	111.7
	Social Good	6	0.848	0.923	0.880	0.880	4.157	4.121	4.121	0.852	0.861	**0.842**	0.848
		8	0.925	1.207	0.947	0.947	0.968	0.931	0.931	0.946	**0.868**	**0.895**	**0.924**
		10	0.987	1.111	1.092	1.092	1.303	1.158	1.158	**0.985**	**0.856**	**0.940**	0.992
		12	1.085	1.203	**1.068**	**1.068**	3.165	3.205	3.205	**1.075**	**0.935**	1.127	**1.054**
	Traffic	6	0.224	0.231	**0.218**	**0.218**	0.355	0.449	0.449	0.236	**0.201**	**0.221**	**0.211**
		8	0.211	0.214	**0.209**	**0.209**	**0.203**	**0.204**	**0.204**	0.250	0.216	**0.207**	**0.202**
		10	0.216	0.406	0.223	0.223	0.231	0.242	0.242	0.229	0.219	**0.215**	**0.206**
		12	0.279	0.332	**0.273**	**0.273**	0.406	0.330	0.330	0.284	**0.268**	**0.268**	**0.268**

Table 58: Multimodal fusion strategies with **DLinear** (+ **LLAMA3**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
DLinear	Agriculture	6	0.112	0.132	0.133	0.133	0.850	1.352	1.188	0.136	0.244	0.136	**0.067**
		8	0.323	**0.187**	**0.187**	**0.187**	1.371	0.884	1.336	**0.210**	0.332	**0.228**	**0.081**
		10	0.163	0.208	0.208	0.208	0.458	0.328	0.240	0.173	0.191	0.198	**0.133**
		12	0.216	0.246	0.250	0.246	0.407	0.289	0.348	**0.162**	0.540	**0.192**	**0.173**
	Climate	6	1.308	**1.307**	**1.274**	**1.231**	1.359	**1.295**	1.344	1.332	**1.160**	**1.215**	**1.075**
		8	1.222	1.345	1.305	1.265	1.310	1.277	1.248	1.268	**1.090**	1.323	**1.108**
		10	1.157	1.356	1.348	1.271	1.196	**1.132**	**1.126**	1.311	**1.083**	1.290	**1.112**
		12	1.202	1.342	1.316	1.303	**1.172**	**1.124**	**1.133**	1.206	**1.152**	1.258	**1.096**
	Economy	6	0.071	0.086	0.086	0.090	13.427	9.363	11.553	0.107	0.501	0.098	**0.027**
		8	0.233	**0.120**	**0.142**	**0.141**	9.724	8.240	9.121	**0.096**	0.412	**0.150**	**0.032**
		10	0.085	0.119	0.129	0.130	1.840	1.176	0.810	0.133	0.295	0.136	**0.047**
		12	0.109	0.129	0.129	0.129	1.582	0.894	0.694	**0.067**	0.605	**0.091**	**0.066**
	Energy	12	0.114	0.203	0.201	0.164	0.238	0.228	0.188	0.117	0.240	0.180	**0.107**
		24	0.218	0.312	0.305	0.280	0.809	0.789	0.678	0.246	0.315	0.258	**0.199**
		36	0.301	0.344	0.369	0.349	1.260	0.936	0.774	0.314	0.344	0.365	**0.282**
		48	0.410	0.427	0.420	**0.405**	0.721	0.676	0.655	0.444	0.439	0.430	**0.386**
	Environment	48	0.489	**0.449**	**0.439**	**0.439**	0.503	**0.476**	**0.482**	0.512	**0.459**	**0.446**	0.494
		96	0.573	**0.466**	**0.482**	**0.479**	**0.539**	**0.499**	**0.479**	**0.568**	**0.465**	**0.463**	**0.572**
		192	0.591	**0.507**	**0.502**	**0.508**	**0.542**	**0.554**	0.616	**0.586**	**0.576**	**0.515**	**0.582**
		336	0.537	**0.515**	**0.498**	**0.495**	**0.512**	**0.502**	**0.494**	**0.537**	**0.506**	**0.497**	**0.537**
	Public Health	12	1.337	1.468	**1.319**	**1.239**	1.341	**1.320**	**1.290**	1.645	1.857	**1.225**	**1.198**
		24	1.577	**1.553**	**1.375**	**1.345**	1.624	**1.557**	**1.568**	1.650	1.997	**1.469**	**1.535**
		36	1.622	1.763	1.627	**1.477**	2.087	1.953	1.887	1.828	1.775	1.641	**1.558**
		48	1.694	1.771	**1.687**	**1.601**	1.830	1.832	1.820	1.766	1.879	**1.618**	**1.664**
	Security	6	104.3	106.1	105.4	105.0	184.5	169.1	171.9	106.1	109.1	104.6	104.8
		8	109.2	109.9	**107.6**	**107.7**	150.5	148.0	147.8	110.4	117.9	**108.5**	**108.9**
		10	110.3	112.9	111.2	110.5	112.6	112.1	112.5	110.9	118.0	110.4	**109.8**
		12	112.0	114.5	113.3	112.6	113.4	112.9	113.4	112.7	119.9	112.6	**111.6**
	Social Good	6	0.999	**0.847**	**0.920**	**0.815**	4.191	2.636	2.642	**0.866**	**0.872**	**0.887**	**0.780**
		8	0.909	0.989	1.097	1.028	2.734	2.493	2.129	**0.906**	0.957	1.058	**0.863**
		10	0.960	1.216	1.124	1.180	1.206	1.070	1.044	1.078	1.030	1.117	0.968
		12	1.080	1.197	1.255	1.264	1.177	1.081	**1.039**	1.142	1.112	1.108	**1.000**
	Traffic	6	0.253	0.275	0.285	0.282	0.505	0.346	0.516	0.308	0.284	0.277	**0.222**
		8	0.322	0.335	0.344	0.340	0.467	0.419	0.454	**0.268**	**0.312**	0.339	**0.221**
		10	0.244	0.328	0.352	0.333	0.345	0.287	0.270	0.261	0.315	0.359	**0.219**
		12	0.289	0.350	0.371	0.360	0.315	0.309	0.301	0.293	0.299	0.317	**0.261**

Table 59: Multimodal fusion strategies with **TiDE** (+ **LLAMA3**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
TiDE	Agriculture	6	0.074	0.074	0.080	0.075	1.699	**0.069**	1.747	**0.061**	**0.065**	**0.062**	**0.061**
		8	0.094	0.099	**0.090**	**0.091**	0.901	0.100	1.004	**0.083**	**0.081**	**0.081**	**0.081**
		10	0.113	18.711	0.113	0.132	50.930	0.117	0.349	**0.103**	**0.103**	**0.103**	**0.104**
		12	0.156	23.792	**0.142**	**0.147**	61.286	**0.148**	0.432	**0.134**	**0.135**	**0.133**	**0.134**
	Climate	6	1.592	**1.589**	1.602	1.649	1.697	**1.454**	**1.475**	**1.257**	**1.244**	**1.235**	**1.249**
		8	1.468	1.536	**1.382**	1.560	**1.133**	1.580	**1.311**	**1.258**	**1.278**	**1.253**	**1.259**
		10	1.398	40.949	1.403	1.532	8.241	1.565	**1.179**	**1.275**	**1.270**	**1.256**	**1.267**
		12	1.500	11.305	**1.407**	**1.498**	3.436	**1.472**	**1.186**	**1.254**	**1.274**	**1.263**	**1.270**
	Economy	6	0.037	0.044	**0.037**	0.037	14.080	0.045	13.600	**0.017**	**0.017**	**0.017**	**0.017**
		8	0.039	0.046	**0.036**	0.040	8.610	**0.031**	9.778	**0.018**	**0.017**	**0.018**	**0.020**
		10	0.030	3.359	0.032	0.040	12.426	0.040	1.512	**0.018**	**0.017**	**0.017**	**0.018**
		12	0.033	4.545	**0.031**	0.037	1.918	0.038	2.290	**0.018**	**0.018**	**0.017**	**0.017**
	Energy	12	0.136	10055.3	0.140	0.176	3650.8	**0.135**	0.291	**0.106**	**0.108**	**0.109**	**0.106**
		24	0.241	0.409	**0.236**	0.306	0.747	**0.238**	0.747	**0.218**	**0.201**	**0.216**	**0.219**
		36	0.328	26053.8	0.332	0.398	14910.8	**0.327**	1.292	**0.295**	**0.296**	**0.296**	**0.294**
		48	0.443	0.483	**0.439**	0.452	0.684	**0.441**	0.688	**0.399**	**0.406**	**0.404**	**0.405**
	Environment	48	0.485	0.733	**0.485**	0.490	0.486	0.486	**0.477**	0.487	**0.485**	**0.485**	**0.484**
		96	0.543	0.698	**0.540**	**0.489**	0.563	0.547	**0.493**	**0.540**	**0.542**	0.543	**0.539**
		192	0.578	14630.4	**0.576**	**0.537**	26545.1	**0.577**	0.621	**0.575**	**0.577**	**0.576**	**0.577**
		336	0.533	40955.4	0.534	**0.517**	17652.0	0.534	**0.489**	**0.533**	0.535	0.534	**0.533**
	Public Health	12	1.297	1640.6	1.311	1.427	1600.4	**1.286**	**1.290**	**1.087**	**1.107**	**1.085**	**1.124**
		24	1.512	2.232	1.532	1.742	**1.500**	1.538	1.635	**1.424**	**1.427**	**1.456**	**1.466**
		36	1.688	26231.0	**1.673**	1.911	9720.8	**1.677**	2.093	**1.619**	**1.619**	**1.599**	**1.625**
		48	1.800	2.321	**1.763**	1.982	1.981	1.804	1.893	**1.732**	**1.741**	**1.700**	**1.719**
	Security	6	146.0	**125.6**	**135.0**	**125.4**	191.8	**122.1**	185.7	**104.8**	**106.9**	**107.0**	**108.0**
		8	129.6	138.3	132.5	138.6	150.1	**128.9**	155.2	**107.8**	**109.4**	**112.2**	**108.5**
		10	132.2	151.2	134.8	135.0	**104.8**	135.2	**117.6**	**113.0**	**110.2**	**113.4**	**111.6**
		12	144.9	153.1	**139.3**	**139.0**	**106.1**	**142.2**	**120.3**	**112.9**	**112.5**	**113.1**	**112.2**
	Social Good	6	0.926	0.979	1.002	1.010	4.407	0.940	4.410	**0.836**	**0.835**	**0.814**	**0.823**
		8	1.098	1.199	**1.032**	1.217	2.748	**1.076**	2.770	**0.965**	**0.952**	**0.953**	**0.956**
		10	1.129	389.2	1.183	1.257	215.8	1.290	**1.067**	**1.112**	**1.063**	**1.085**	**1.072**
		12	1.224	536.6	**1.218**	1.256	155.4	1.265	**1.161**	**1.150**	**1.143**	**1.156**	**1.143**
	Traffic	6	0.289	0.298	0.295	**0.275**	0.559	0.301	0.461	**0.237**	**0.236**	**0.236**	**0.233**
		8	0.303	0.340	**0.277**	0.310	0.451	**0.272**	0.371	**0.231**	**0.230**	**0.233**	**0.223**
		10	0.251	42.214	**0.249**	0.321	14.641	0.296	0.273	**0.224**	**0.231**	**0.225**	**0.228**
		12	0.319	58.262	**0.305**	0.333	49.699	0.329	**0.293**	**0.288**	**0.290**	**0.284**	**0.289**

Table 60: Multimodal fusion strategies with **FiLM** (+ **LLAMA3**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	CFA
FiLM	Agriculture	6	0.060	0.084	0.068	0.068	1.740	0.063	1.854	**0.060**	0.061	0.062	0.062
		8	0.082	0.108	0.091	0.087	3.002	0.089	1.176	**0.080**	**0.082**	**0.080**	**0.079**
		10	0.106	22.421	**0.104**	0.115	1.026	0.109	0.321	0.112	**0.104**	**0.103**	**0.105**
		12	0.138	20.331	0.141	**0.131**	0.307	0.144	0.418	**0.135**	**0.136**	**0.136**	0.141
	Climate	6	1.354	**1.262**	**1.306**	**1.313**	**1.313**	**1.269**	**1.286**	**1.241**	**1.288**	**1.248**	**1.231**
		8	1.283	1.456	1.286	1.292	**1.039**	1.345	**1.226**	1.283	1.296	**1.265**	**1.266**
		10	1.284	14.615	1.294	1.296	**1.168**	1.307	**1.092**	**1.276**	1.293	**1.270**	**1.273**
		12	1.276	11.715	1.284	1.329	7.656	1.287	**1.106**	1.298	1.293	1.277	**1.268**
	Economy	6	0.017	0.049	0.019	0.037	21.726	0.019	17.804	0.019	**0.016**	0.019	**0.017**
		8	0.018	0.033	0.021	0.020	11.414	0.020	10.334	**0.017**	**0.018**	**0.017**	**0.017**
		10	0.019	0.024	0.020	0.019	1.269	0.019	2.252	0.019	**0.018**	**0.018**	**0.018**
		12	0.018	3.131	0.019	0.029	0.717	0.020	2.128	**0.018**	**0.018**	**0.018**	**0.017**
	Energy	12	0.122	8155.3	0.131	0.169	0.326	0.132	0.217	**0.109**	**0.111**	0.128	**0.110**
		24	0.230	1.468	0.237	0.304	0.822	0.257	0.756	**0.217**	**0.222**	**0.228**	**0.218**
		36	0.312	0.399	0.357	0.446	1.315	0.387	1.195	0.315	0.318	0.328	**0.311**
		48	0.428	0.495	0.460	0.523	0.743	0.510	0.690	**0.419**	0.432	0.477	**0.427**
	Environment	48	0.491	949097920.0	**0.486**	**0.475**	0.518	**0.470**	0.530	**0.487**	**0.467**	**0.485**	**0.488**
		96	0.547	556371.0	**0.483**	**0.479**	0.604	**0.491**	0.566	**0.546**	**0.509**	**0.509**	**0.544**
		192	0.574	2790298624.0	**0.518**	**0.521**	1.243	**0.525**	0.642	**0.574**	**0.550**	**0.522**	**0.566**
		336	0.529	1012101632.0	0.540	**0.524**	81147368.0	**0.491**	**0.488**	**0.527**	**0.503**	**0.527**	**0.527**
	Public Health	12	1.157	2.965	1.402	1.296	2.071	1.401	**1.080**	**1.127**	**1.138**	1.311	**1.107**
		24	1.606	**1.525**	1.737	**1.354**	2.231	**1.585**	**1.599**	**1.453**	**1.488**	**1.573**	**1.453**
		36	1.618	1.774	1.810	1.908	2.315	1.698	1.838	1.894	1.704	1.671	1.644
		48	1.706	2.329	1.748	2.137	1.771	1.892	**1.659**	1.736	1.784	1.712	1.735
	Security	6	127.4	**110.9**	**102.2**	**101.1**	207.3	**103.0**	189.1	**102.8**	**103.1**	**104.6**	**107.0**
		8	113.8	117.5	**105.7**	116.5	136.6	**105.6**	161.8	115.9	**104.4**	**106.5**	**105.1**
		10	116.9	136.1	**107.9**	133.4	**101.7**	**108.0**	**111.7**	**109.4**	**111.1**	**108.9**	**115.0**
		12	119.1	137.6	**110.1**	**108.2**	**103.3**	**109.9**	**112.9**	**113.2**	**112.3**	**109.7**	**113.8**
	Social Good	6	0.867	136.5	**0.866**	**0.860**	4.180	0.873	4.340	**0.828**	**0.828**	**0.849**	**0.814**
		8	1.003	1.684	**0.937**	1.044	2.679	**0.951**	2.863	**0.991**	**0.915**	**0.956**	**0.960**
		10	1.139	599.9	**1.042**	1.222	266.7	**1.041**	**1.122**	**1.024**	**1.059**	**1.019**	**1.116**
		12	1.230	723.8	**1.115**	**1.148**	201.7	**1.120**	**1.118**	**1.223**	**1.189**	**1.066**	**1.166**
	Traffic	6	0.228	0.269	**0.227**	0.239	0.961	0.233	0.514	0.243	0.238	0.244	0.241
		8	0.223	**0.211**	**0.212**	**0.215**	2.486	0.228	0.397	0.228	**0.222**	**0.219**	0.235
		10	0.216	0.221	**0.216**	**0.209**	0.820	0.218	0.256	0.235	0.221	**0.214**	**0.216**
		12	0.253	3.208	**0.249**	0.263	1.060	0.262	**0.246**	0.283	0.260	0.273	**0.249**

Table 61: Multimodal fusion strategies with **FEDformer** (+ **LLAMA3**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
FEDformer	Agriculture	6	0.056	0.060	0.064	0.061	0.063	0.061	0.932	0.065	0.067	**0.056**	0.057
		8	0.073	0.078	**0.073**	0.094	0.087	**0.073**	0.969	**0.072**	**0.069**	0.082	**0.070**
		10	0.087	0.107	0.100	0.092	0.104	0.102	0.327	0.107	0.096	0.091	0.088
		12	0.111	0.131	0.127	0.143	0.133	0.121	0.460	0.127	0.122	0.134	0.113
	Climate	6	1.102	1.141	1.122	**1.057**	**1.055**	**1.069**	1.279	**1.052**	**1.096**	**1.083**	1.108
		8	1.091	**1.047**	**1.091**	1.123	**1.042**	**1.023**	1.105	1.092	**1.069**	**1.063**	**1.034**
		10	1.085	1.087	1.163	**1.072**	**1.049**	1.086	**0.915**	1.156	1.109	1.085	**1.073**
		12	1.106	**1.104**	1.115	**1.101**	**1.096**	1.151	**0.950**	1.114	**1.089**	**1.089**	**1.088**
	Economy	6	0.039	0.049	0.050	**0.036**	0.045	0.045	9.237	0.050	0.051	**0.033**	0.049
		8	0.047	**0.040**	**0.042**	0.056	**0.027**	0.051	7.025	**0.042**	**0.036**	**0.047**	0.050
		10	0.039	0.045	0.043	0.041	0.060	**0.032**	1.445	0.043	0.042	**0.036**	0.045
		12	0.055	0.059	**0.039**	0.062	**0.046**	**0.033**	1.301	**0.039**	**0.039**	**0.032**	**0.048**
	Energy	12	0.102	0.133	0.111	0.141	0.118	0.118	0.260	0.111	0.114	**0.098**	**0.094**
		24	0.182	0.199	0.237	0.303	0.248	0.187	0.767	0.227	0.244	0.190	**0.181**
		36	0.258	0.351	0.379	0.403	0.371	0.305	1.302	0.305	0.348	0.335	**0.254**
		48	0.366	0.440	0.367	0.446	0.468	0.458	0.705	0.502	0.466	0.466	0.409
	Environment	48	0.463	0.493	0.496	0.501	0.514	0.489	0.491	0.491	0.514	0.501	0.481
		96	0.489	**0.476**	**0.474**	0.498	**0.479**	**0.478**	**0.459**	0.507	0.497	0.504	**0.480**
		192	0.493	0.535	0.493	**0.481**	0.527	0.502	**0.478**	**0.485**	0.499	0.495	**0.484**
		336	0.461	0.504	0.475	0.483	0.490	0.472	**0.455**	0.480	0.482	0.489	0.481
	Public Health	12	1.142	**1.037**	**1.059**	**1.101**	1.175	**1.062**	**1.055**	**1.109**	**1.040**	**1.028**	**1.092**
		24	1.379	1.436	1.422	1.413	1.545	1.474	1.401	1.440	1.486	1.431	1.405
		36	1.438	1.660	1.558	1.530	1.710	1.474	1.639	1.464	1.491	1.551	1.452
		48	1.572	1.690	1.699	1.621	1.770	1.698	**1.496**	1.716	**1.447**	1.672	**1.542**
	Security	6	106.0	110.1	106.5	113.3	106.1	**104.8**	166.4	106.5	114.8	**101.2**	107.2
		8	111.6	**108.8**	**107.9**	**108.4**	**110.4**	**109.0**	141.3	**108.0**	**111.1**	**109.5**	**109.8**
		10	111.5	112.8	111.7	**107.6**	112.8	117.3	116.3	111.7	112.4	**107.8**	115.3
		12	117.8	**115.8**	**115.4**	**113.6**	**114.3**	**116.0**	118.1	**115.4**	**112.6**	**106.2**	**114.4**
	Social Good	6	0.883	**0.805**	**0.837**	**0.837**	**0.873**	**0.861**	4.382	**0.798**	**0.843**	**0.863**	**0.879**
		8	0.905	**0.875**	**0.874**	0.916	0.911	**0.854**	2.811	**0.890**	**0.863**	**0.888**	**0.869**
		10	0.954	0.967	**0.903**	**0.895**	1.142	**0.919**	1.140	**0.905**	**0.944**	**0.903**	**0.936**
		12	1.073	**0.991**	**1.025**	**1.061**	1.161	**0.973**	1.147	**1.028**	**1.026**	**0.963**	**1.067**
	Traffic	6	0.152	0.158	0.153	**0.151**	0.157	**0.151**	0.394	0.156	0.154	0.159	**0.149**
		8	0.156	0.163	0.158	0.162	**0.150**	0.157	0.318	0.158	0.157	**0.155**	0.158
		10	0.162	0.176	0.168	0.164	**0.148**	0.165	0.198	0.168	0.166	**0.158**	0.165
		12	0.228	0.235	0.234	0.239	**0.208**	**0.224**	**0.212**	0.230	**0.224**	**0.220**	**0.224**

Table 62: Multimodal fusion strategies with **Autoformer** (+ **LLAMA3**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Autoformer	Agriculture	6	0.071	0.076	0.083	0.094	0.072	0.073	0.877	0.076	0.079	**0.071**	**0.063**
		8	0.088	**0.086**	0.089	0.091	**0.083**	0.090	1.316	0.095	0.100	**0.083**	**0.084**
		10	0.102	0.113	0.123	0.121	0.110	**0.099**	0.281	0.124	0.121	0.109	**0.101**
		12	0.132	0.137	0.163	0.151	0.136	0.144	0.201	0.163	0.148	0.145	0.134
	Climate	6	1.249	1.282	1.251	1.295	**1.190**	**1.229**	1.365	1.250	**1.247**	**1.199**	**1.204**
		8	1.186	1.239	1.303	1.217	1.252	**1.171**	1.263	1.233	1.199	**1.179**	**1.185**
		10	1.193	1.307	1.219	1.280	1.280	1.232	**0.998**	1.235	1.260	1.237	1.193
		12	1.161	1.222	1.207	1.246	1.205	1.242	**1.007**	1.174	1.246	1.231	**1.135**
	Economy	6	0.061	0.072	**0.050**	**0.059**	0.065	**0.050**	10.519	**0.050**	**0.060**	**0.054**	**0.044**
		8	0.063	0.082	0.064	**0.054**	0.066	0.073	8.158	0.064	0.075	**0.057**	0.064
		10	0.071	**0.067**	**0.052**	**0.064**	0.091	**0.052**	1.633	**0.048**	**0.065**	**0.052**	**0.039**
		12	0.076	**0.065**	**0.053**	**0.057**	**0.069**	**0.053**	1.204	**0.049**	**0.055**	**0.051**	**0.053**
	Energy	12	0.106	0.124	0.139	0.148	0.183	0.136	0.312	0.155	0.138	0.147	0.144
		24	0.278	0.322	0.298	0.318	0.330	**0.274**	0.827	0.313	0.313	0.290	0.290
		36	0.378	0.391	0.391	0.398	0.386	**0.373**	1.231	0.402	0.383	0.387	**0.377**
		48	0.481	0.484	0.485	**0.471**	**0.479**	0.487	0.711	0.494	**0.476**	0.492	**0.468**
	Environment	48	0.540	**0.523**	**0.492**	**0.507**	**0.516**	**0.499**	**0.498**	**0.510**	**0.500**	**0.507**	**0.463**
		96	0.544	0.545	**0.496**	**0.497**	**0.515**	**0.513**	**0.517**	**0.509**	**0.523**	**0.505**	**0.473**
		192	0.595	**0.565**	**0.535**	**0.524**	**0.571**	**0.516**	0.604	**0.534**	**0.537**	**0.504**	**0.501**
		336	0.512	0.548	0.534	0.526	0.539	0.542	**0.500**	0.539	0.528	0.541	0.515
	Public Health	12	1.583	**1.416**	**1.444**	**1.581**	1.768	1.704	**1.445**	**1.468**	**1.448**	1.615	**1.387**
		24	1.919	2.096	2.022	**1.896**	**1.841**	**1.832**	**1.451**	**1.862**	**1.810**	**1.800**	**1.790**
		36	1.920	2.003	**1.839**	1.974	2.121	1.925	2.019	1.940	**1.804**	2.048	1.942
		48	1.885	2.070	1.925	1.968	1.997	1.892	**1.621**	2.053	**1.855**	2.006	**1.831**
	Security	6	106.7	107.0	108.4	**105.8**	**104.9**	109.7	147.0	108.4	108.6	111.0	110.2
		8	111.0	**108.1**	**110.5**	112.0	**110.6**	112.3	139.0	**110.5**	112.9	**105.0**	**110.1**
		10	116.2	116.5	116.3	**113.4**	**111.5**	**110.8**	117.0	116.3	**115.4**	**113.0**	**112.1**
		12	117.2	**117.1**	**115.4**	**114.7**	**115.4**	118.0	118.0	**113.6**	**115.2**	**116.3**	**112.8**
	Social Good	6	0.861	0.905	**0.818**	**0.839**	**0.829**	0.883	4.404	**0.846**	0.868	**0.815**	0.873
		8	1.001	1.008	**0.982**	**0.991**	1.064	1.006	2.742	**0.994**	**0.973**	**0.955**	**0.970**
		10	1.018	1.114	1.121	1.081	1.046	1.035	1.132	1.123	1.073	1.032	**1.007**
		12	1.059	1.258	1.142	1.127	1.160	1.173	1.148	1.128	1.214	**1.026**	1.067
	Traffic	6	0.179	0.191	0.179	**0.177**	0.191	0.184	0.370	0.185	**0.161**	**0.176**	0.190
		8	0.186	**0.183**	0.193	**0.178**	0.236	**0.171**	0.298	0.195	0.202	**0.184**	0.204
		10	0.199	0.205	**0.191**	0.206	0.217	**0.188**	0.204	**0.191**	**0.186**	**0.195**	**0.188**
		12	0.261	**0.253**	**0.216**	**0.253**	**0.251**	**0.220**	**0.251**	**0.230**	**0.243**	**0.220**	0.264

Table 63: Multimodal fusion strategies with **Crossformer** (+ **LLAMA3**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Crossformer	Agriculture	6	0.175	**0.154**	0.183	**0.115**	**0.141**	0.245	**0.158**	0.180	0.187	**0.118**	**0.153**
		8	0.214	**0.195**	**0.212**	0.222	0.659	0.305	**0.172**	0.245	0.245	**0.142**	0.263
		10	0.322	**0.260**	**0.248**	0.392	**0.212**	0.334	**0.316**	**0.253**	**0.304**	**0.273**	0.350
		12	0.332	0.414	**0.323**	0.420	0.486	0.455	0.527	0.414	**0.269**	0.390	**0.323**
	Climate	6	1.041	1.091	1.138	1.042	1.067	1.049	1.068	1.047	1.064	**1.020**	1.045
		8	1.066	1.081	1.095	1.081	**1.052**	1.086	1.086	1.080	1.091	1.068	**1.058**
		10	1.095	**1.090**	1.096	**1.094**	1.100	**1.084**	1.100	1.103	1.095	**1.091**	1.095
		12	1.099	1.109	**1.095**	**1.081**	1.146	**1.075**	1.100	**1.088**	1.106	**1.063**	1.109
	Economy	6	0.367	0.386	**0.293**	**0.290**	**0.211**	**0.298**	0.550	0.407	0.452	**0.208**	**0.234**
		8	0.402	0.690	0.464	0.554	5.684	0.662	0.987	0.518	**0.163**	**0.151**	**0.199**
		10	0.468	0.807	**0.447**	0.751	**0.389**	0.660	0.755	**0.358**	**0.227**	0.675	0.492
		12	0.344	0.843	0.984	0.841	0.498	0.971	0.802	0.857	0.720	0.521	**0.189**
	Energy	12	0.139	0.139	0.173	**0.137**	0.160	0.145	**0.131**	**0.137**	0.150	0.153	0.144
		24	0.225	0.226	0.254	0.276	0.272	0.277	0.264	0.255	0.264	0.258	0.250
		36	0.333	0.375	0.361	**0.325**	0.355	0.348	0.351	**0.308**	**0.332**	0.340	**0.326**
		48	0.435	0.444	**0.398**	**0.410**	**0.427**	**0.417**	**0.389**	**0.428**	**0.411**	0.438	**0.432**
	Environment	48	0.489	**0.453**	**0.466**	**0.473**	**0.436**	**0.442**	**0.483**	**0.457**	**0.443**	**0.468**	**0.448**
		96	0.536	**0.446**	**0.477**	**0.483**	**0.449**	**0.457**	**0.485**	**0.455**	**0.462**	**0.467**	**0.463**
		192	0.550	**0.509**	0.552	0.567	0.561	**0.545**	**0.537**	**0.515**	**0.491**	0.554	**0.489**
		336	0.538	**0.491**	**0.521**	**0.510**	**0.507**	0.548	0.551	**0.526**	**0.515**	0.581	**0.502**
	Public Health	12	1.070	1.136	1.071	1.074	1.465	1.132	1.086	**1.066**	**1.050**	1.097	**0.975**
		24	1.336	1.426	**1.306**	1.352	1.352	1.394	1.379	1.350	1.400	**1.314**	1.420
		36	1.390	1.411	**1.356**	**1.345**	1.409	1.455	**1.332**	**1.379**	**1.329**	**1.364**	**1.357**
		48	1.509	**1.462**	**1.451**	**1.433**	**1.505**	**1.458**	1.569	**1.438**	**1.452**	**1.421**	**1.397**
	Security	6	121.3	123.3	123.3	122.3	121.3	**119.0**	124.0	123.3	121.7	121.3	**121.0**
		8	120.7	126.5	124.5	125.9	132.4	127.0	126.8	123.6	123.3	125.2	122.1
		10	123.8	128.0	126.1	125.9	**122.2**	128.8	127.6	125.6	124.0	126.3	124.6
		12	127.3	127.8	128.6	127.3	129.4	128.5	129.3	128.5	**126.3**	127.6	**127.2**
	Social Good	6	0.754	**0.730**	**0.741**	**0.752**	0.766	**0.752**	**0.744**	0.757	**0.732**	**0.743**	**0.750**
		8	0.810	0.821	0.823	0.811	1.895	**0.803**	0.833	0.822	0.841	0.837	0.828
		10	0.898	0.964	**0.884**	**0.860**	0.933	0.904	**0.870**	**0.882**	**0.874**	**0.877**	**0.869**
		12	0.950	0.978	**0.919**	**0.937**	0.967	**0.914**	**0.947**	**0.941**	**0.938**	**0.916**	**0.943**
	Traffic	6	0.213	0.215	0.217	**0.213**	**0.209**	0.217	0.218	0.220	0.232	0.215	0.216
		8	0.203	0.214	0.220	0.223	0.311	0.223	0.212	0.209	0.218	0.213	0.218
		10	0.216	**0.213**	0.235	**0.214**	0.217	**0.200**	0.217	0.224	0.218	0.226	0.222
		12	0.239	0.240	0.242	0.261	0.271	**0.234**	0.249	0.253	0.249	0.241	0.249

Table 64: Multimodal fusion strategies with **Reformer** (+ **LLAMA3**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Reformer	Agriculture	6	0.193	**0.188**	0.251	**0.174**	0.273	**0.154**	0.359	**0.185**	0.248	0.260	0.193
		8	0.248	0.338	0.328	0.280	0.347	0.415	**0.245**	0.273	**0.161**	**0.214**	0.266
		10	0.179	0.674	0.281	0.314	0.544	0.413	0.744	0.259	0.268	0.493	0.419
		12	0.474	**0.333**	**0.430**	**0.358**	0.634	**0.283**	**0.295**	**0.244**	0.599	**0.305**	**0.241**
	Climate	6	1.013	1.013	1.062	1.043	1.038	**1.008**	1.068	1.026	1.030	**1.000**	1.071
		8	1.077	**1.076**	**1.061**	1.106	**1.059**	1.084	**0.926**	**1.037**	**1.066**	**1.044**	1.079
		10	1.063	1.089	1.109	1.079	1.078	1.078	**0.993**	1.098	1.087	1.093	1.098
		12	1.098	**1.067**	**1.098**	**1.046**	1.124	**1.089**	**1.040**	1.099	1.104	**1.086**	1.101
	Economy	6	0.348	**0.226**	**0.293**	0.389	0.677	**0.331**	0.948	**0.292**	**0.336**	**0.190**	**0.264**
		8	0.212	**0.207**	0.492	**0.212**	0.420	0.836	1.061	0.493	0.445	0.575	0.289
		10	0.562	1.376	0.690	**0.120**	1.962	0.596	1.686	**0.234**	**0.388**	1.085	**0.043**
		12	0.766	1.163	**0.672**	**0.180**	1.671	1.125	**0.748**	1.113	1.135	**0.364**	0.969
	Energy	12	0.235	**0.215**	**0.221**	0.303	**0.227**	0.251	**0.226**	**0.150**	**0.167**	**0.222**	**0.217**
		24	0.401	0.424	0.409	**0.381**	0.434	**0.395**	**0.351**	**0.351**	**0.263**	**0.303**	**0.353**
		36	0.462	0.485	**0.456**	**0.459**	0.501	0.475	**0.423**	0.493	**0.442**	**0.412**	**0.408**
		48	0.485	0.564	0.536	0.525	0.740	0.509	0.584	0.538	0.495	0.532	0.507
	Environment	48	0.411	0.424	0.424	0.428	0.413	0.422	0.411	**0.407**	**0.408**	0.411	**0.409**
		96	0.473	**0.444**	**0.412**	**0.434**	**0.469**	**0.418**	**0.430**	**0.405**	**0.395**	**0.437**	**0.412**
		192	0.458	**0.439**	**0.420**	**0.451**	**0.403**	**0.444**	**0.430**	**0.433**	**0.395**	**0.422**	**0.407**
		336	0.451	**0.423**	**0.421**	**0.433**	**0.450**	**0.433**	**0.435**	**0.413**	**0.404**	**0.419**	**0.421**
	Public Health	12	1.244	**1.119**	**1.185**	**1.189**	1.420	**1.097**	**1.203**	**1.020**	**1.062**	**1.083**	**1.082**
		24	1.233	1.482	1.337	1.380	1.330	1.382	1.308	1.317	1.240	1.294	1.267
		36	1.366	1.601	1.394	1.500	**1.350**	1.436	**1.210**	**1.296**	**1.322**	**1.319**	**1.250**
		48	1.427	1.525	**1.364**	**1.324**	**1.416**	1.584	1.498	**1.364**	1.463	1.585	1.471
	Security	6	124.6	**123.6**	**123.6**	**124.2**	**118.5**	**121.7**	**122.1**	**123.6**	**124.1**	**123.7**	**123.4**
		8	123.9	**118.0**	**122.5**	124.2	**119.0**	**123.0**	125.0	**122.5**	**122.6**	124.2	125.5
		10	127.2	**124.4**	**124.6**	**122.4**	130.0	**125.5**	**127.1**	**125.8**	**123.8**	**125.1**	**125.2**
		12	123.4	126.1	126.0	126.5	125.5	125.1	126.8	126.0	125.8	126.0	126.6
	Social Good	6	0.805	**0.787**	**0.799**	0.855	0.840	0.835	0.869	**0.795**	0.831	0.818	0.824
		8	0.877	**0.842**	0.892	0.889	**0.876**	0.878	0.938	0.889	0.899	**0.849**	0.889
		10	0.936	0.960	0.990	0.956	1.018	**0.918**	0.970	0.990	0.959	0.938	**0.935**
		12	1.052	**0.955**	**1.039**	**1.004**	1.089	**1.033**	**0.989**	**1.012**	**0.954**	**1.039**	**0.988**
	Traffic	6	0.208	0.241	0.247	0.222	0.235	0.281	0.257	0.248	0.243	0.250	0.237
		8	0.236	0.288	0.269	0.247	**0.217**	0.259	**0.217**	0.268	**0.234**	0.257	**0.231**
		10	0.253	0.260	0.257	**0.231**	**0.238**	0.263	**0.236**	0.258	0.257	**0.248**	0.260
		12	0.248	0.268	0.285	0.281	0.258	0.322	**0.244**	0.282	0.275	0.282	0.284

Table 65: Multimodal fusion strategies with **Informer** (+ **LLAMA3**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Informer	Agriculture	6	0.264	0.362	0.327	0.304	**0.261**	0.289	0.270	**0.212**	**0.216**	**0.234**	**0.243**
		8	0.450	**0.386**	**0.361**	**0.376**	**0.171**	**0.414**	**0.269**	**0.272**	**0.388**	**0.195**	**0.241**
		10	0.402	0.412	0.440	**0.323**	0.574	**0.251**	**0.339**	**0.299**	**0.343**	**0.305**	0.434
		12	0.507	0.648	0.520	0.530	**0.471**	0.639	**0.494**	0.583	0.574	**0.420**	0.543
	Climate	6	0.994	1.084	1.068	1.072	1.035	1.114	1.027	1.064	1.080	1.043	1.078
		8	1.058	**0.982**	1.105	1.081	**0.923**	1.068	1.112	1.074	1.093	1.067	1.083
		10	1.084	1.101	1.100	**1.060**	**1.042**	**1.066**	1.089	**1.076**	**1.048**	1.091	1.092
		12	1.068	1.091	1.083	1.106	**0.889**	**1.014**	1.096	1.097	1.071	1.111	1.092
	Economy	6	0.707	0.869	**0.396**	**0.567**	**0.544**	**0.624**	**0.583**	**0.530**	**0.642**	**0.628**	**0.254**
		8	0.815	**0.812**	**0.756**	**0.520**	**0.275**	**0.275**	**0.781**	**0.261**	**0.143**	**0.452**	**0.648**
		10	0.807	0.824	0.999	**0.714**	1.228	1.153	1.049	**0.596**	**0.619**	**0.633**	0.832
		12	1.093	1.445	**1.031**	1.181	**0.666**	**0.179**	1.205	**0.950**	**0.616**	1.429	**0.967**
	Energy	12	0.146	0.158	0.218	0.190	0.261	0.182	0.208	0.162	0.161	0.158	0.168
		24	0.273	**0.269**	0.320	0.320	**0.256**	0.275	0.327	0.304	**0.263**	0.297	0.304
		36	0.373	**0.358**	**0.357**	0.408	0.389	**0.351**	0.425	**0.328**	**0.351**	**0.306**	**0.369**
		48	0.499	**0.489**	0.522	**0.494**	**0.410**	**0.490**	**0.429**	**0.398**	**0.402**	**0.466**	**0.433**
	Environment	48	0.430	**0.418**	0.469	0.446	0.443	0.464	0.474	0.442	0.438	0.430	0.450
		96	0.421	0.484	0.449	0.444	0.444	0.442	0.439	0.430	0.440	0.452	0.444
		192	0.467	0.489	**0.435**	0.508	**0.437**	0.509	0.478	0.498	0.493	**0.465**	**0.459**
		336	0.457	0.477	0.470	0.482	**0.427**	0.469	0.487	0.513	0.486	0.478	**0.426**
	Public Health	12	1.114	1.270	1.252	**0.982**	1.545	**1.100**	**1.010**	**1.003**	**1.103**	1.287	1.141
		24	1.272	1.621	1.303	**1.200**	1.314	1.344	**1.228**	1.382	1.278	1.369	1.302
		36	1.490	**1.465**	1.493	**1.454**	**1.313**	**1.414**	**1.438**	**1.314**	1.551	1.552	1.517
		48	1.619	**1.403**	1.755	1.659	**1.326**	1.726	**1.570**	**1.599**	1.701	**1.592**	**1.606**
	Security	6	122.5	126.0	**122.3**	123.9	125.0	126.7	122.7	125.6	**122.0**	127.5	124.8
		8	130.2	**129.3**	**129.2**	**126.2**	**129.7**	**127.0**	**128.1**	**128.9**	**128.4**	**126.8**	**126.9**
		10	130.4	130.8	**129.6**	**127.9**	130.5	**124.0**	**129.0**	**128.9**	**129.4**	**128.0**	**130.1**
		12	131.4	132.0	**127.9**	**130.8**	**128.4**	**130.0**	**129.8**	**131.1**	**130.2**	132.1	**130.3**
	Social Good	6	0.749	**0.746**	0.764	**0.728**	0.764	0.795	**0.747**	0.812	**0.748**	0.789	0.751
		8	0.793	**0.776**	0.830	0.862	0.842	0.838	0.808	0.845	0.835	0.858	0.810
		10	0.828	0.890	0.897	0.874	0.864	0.882	0.918	0.886	0.894	0.895	0.872
		12	0.980	**0.888**	**0.915**	**0.866**	1.062	**0.893**	**0.919**	**0.913**	**0.896**	**0.946**	**0.948**
	Traffic	6	0.172	0.187	**0.165**	**0.163**	**0.154**	**0.162**	**0.144**	**0.169**	**0.161**	**0.166**	**0.169**
		8	0.171	**0.161**	**0.162**	**0.160**	**0.162**	**0.167**	**0.158**	0.180	0.189	**0.163**	**0.160**
		10	0.187	0.189	0.217	0.200	**0.175**	0.189	**0.185**	**0.164**	0.204	**0.173**	0.197
		12	0.208	0.210	0.218	0.213	**0.202**	0.221	**0.204**	0.219	0.210	0.224	0.215

Table 66: Multimodal fusion strategies with **TSMixer** (+ **LLAMA3**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
TSMixer	Agriculture	6	0.102	**0.086**	0.119	0.104	0.121	**0.094**	**0.100**	0.112	0.162	**0.098**	**0.085**
		8	0.103	0.150	0.171	0.330	0.242	0.316	0.180	**0.103**	0.264	0.238	0.105
		10	0.395	0.486	0.892	0.469	**0.294**	0.937	0.497	0.481	0.778	0.422	**0.229**
		12	0.617	1.109	1.245	**0.606**	1.374	**0.562**	**0.494**	0.674	1.386	1.206	**0.337**
	Climate	6	1.069	**1.060**	1.079	1.138	1.077	1.088	1.187	**1.063**	**1.067**	**1.062**	**1.067**
		8	1.094	**1.086**	**1.080**	1.232	**1.077**	1.156	1.162	**1.089**	1.097	**1.082**	**1.083**
		10	1.102	1.158	1.186	1.204	1.108	1.127	**1.099**	1.147	1.112	1.132	**1.101**
		12	1.109	1.124	1.140	1.174	1.154	**1.094**	1.146	1.144	1.158	1.140	**1.106**
	Economy	6	0.054	0.062	0.073	0.093	0.106	0.143	0.126	0.153	0.141	0.094	0.063
		8	0.078	0.268	0.219	0.276	0.807	0.348	0.141	0.227	0.215	0.100	**0.068**
		10	0.263	1.509	1.802	1.775	0.266	1.992	0.318	0.593	1.003	1.229	**0.085**
		12	0.917	2.240	1.976	1.931	2.472	**0.672**	1.146	**0.590**	2.820	2.374	**0.173**
	Energy	12	0.142	**0.138**	**0.135**	0.159	0.151	**0.142**	0.161	0.151	**0.137**	**0.141**	0.148
		24	0.261	0.287	0.297	0.329	0.266	**0.236**	0.303	**0.250**	0.283	0.287	0.268
		36	0.355	**0.330**	0.410	0.479	**0.315**	0.360	0.363	**0.349**	0.380	**0.331**	0.372
		48	0.451	**0.412**	**0.435**	0.695	**0.428**	0.583	**0.448**	**0.416**	**0.410**	**0.444**	0.460
	Environment	48	0.542	**0.432**	**0.450**	**0.454**	**0.436**	**0.442**	**0.453**	**0.520**	**0.455**	**0.437**	**0.509**
		96	0.606	**0.456**	**0.466**	**0.485**	**0.456**	**0.457**	**0.486**	**0.581**	**0.439**	**0.471**	**0.559**
		192	0.638	**0.531**	**0.472**	**0.539**	**0.599**	**0.523**	**0.511**	**0.591**	**0.448**	**0.495**	0.656
		336	0.588	0.652	**0.452**	**0.543**	**0.522**	**0.538**	**0.512**	**0.582**	**0.496**	**0.484**	**0.580**
	Public Health	12	1.155	**1.117**	1.173	1.392	1.296	1.251	1.209	**1.155**	1.178	1.158	**1.129**
		24	1.428	1.649	**1.388**	1.483	**1.347**	1.471	1.450	**1.315**	1.667	**1.345**	**1.377**
		36	1.479	1.749	1.613	1.581	1.501	1.503	1.549	**1.474**	1.693	1.556	**1.439**
		48	1.599	**1.543**	1.777	1.633	1.607	1.687	1.673	1.625	**1.584**	1.725	**1.529**
	Security	6	128.3	**127.8**	**127.8**	**126.4**	**125.9**	**123.9**	130.0	**124.0**	**127.8**	**128.0**	**128.0**
		8	127.9	**125.8**	**127.3**	128.6	**125.2**	**122.6**	131.8	129.1	**126.3**	**127.1**	**127.0**
		10	129.3	**129.1**	132.8	131.0	**126.8**	132.4	129.3	**129.1**	131.4	131.9	**128.8**
		12	131.8	133.6	133.3	132.3	133.2	**127.9**	**131.3**	133.9	134.5	132.4	**131.6**
	Social Good	6	0.749	0.795	0.861	0.779	**0.732**	**0.731**	1.043	0.842	0.835	0.792	**0.741**
		8	0.827	0.875	0.886	0.903	0.883	0.850	0.845	0.843	0.945	**0.810**	**0.824**
		10	0.906	0.921	**0.878**	1.057	1.004	0.921	0.942	0.959	1.141	**0.878**	**0.873**
		12	1.091	**1.041**	**1.014**	**0.975**	**1.053**	**1.016**	**0.979**	**0.952**	1.265	**0.924**	**0.847**
	Traffic	6	0.203	0.219	0.222	0.239	0.221	0.216	0.224	0.259	0.255	0.252	**0.188**
		8	0.216	0.260	0.266	0.253	0.246	0.251	0.220	0.259	0.307	0.239	**0.195**
		10	0.228	0.331	0.570	0.291	0.247	0.532	0.237	0.260	0.290	0.344	**0.207**
		12	0.293	0.640	0.692	0.312	0.713	**0.281**	**0.291**	0.352	0.779	0.481	**0.249**

Table 67: Multimodal fusion strategies with **Transformer** (+ **LLAMA3**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Transformer	Agriculture	6	0.128	**0.090**	**0.127**	0.179	0.132	0.211	0.267	0.144	0.170	0.181	0.131
		8	0.173	0.230	0.278	**0.137**	**0.157**	0.266	0.285	0.277	0.193	0.181	**0.148**
		10	0.182	0.418	0.279	0.224	**0.130**	0.234	0.571	0.291	0.205	0.325	0.214
		12	0.238	0.293	**0.218**	0.437	**0.158**	**0.198**	0.382	**0.219**	**0.221**	0.514	0.272
	Climate	6	1.032	1.037	1.080	**1.001**	**0.955**	1.081	**0.980**	1.080	**1.009**	**1.018**	1.047
		8	1.059	1.064	1.080	1.063	**1.031**	**1.040**	**1.012**	1.079	**1.039**	**1.034**	**0.982**
		10	1.066	**1.041**	**1.064**	1.071	1.098	1.083	**0.994**	**1.064**	**1.062**	**1.030**	1.071
		12	1.035	1.103	1.081	1.071	1.098	1.062	1.042	1.082	1.102	1.067	1.081
	Economy	6	0.401	**0.283**	**0.059**	**0.338**	**0.140**	**0.226**	0.592	**0.061**	**0.202**	**0.145**	**0.127**
		8	0.076	0.413	0.403	0.103	**0.061**	0.252	0.882	0.087	**0.061**	**0.050**	0.163
		10	0.075	0.357	0.252	0.737	**0.070**	0.160	1.317	0.123	0.568	0.278	0.228
		12	0.319	**0.143**	0.432	**0.196**	**0.140**	**0.274**	0.670	**0.303**	0.416	**0.116**	**0.043**
	Energy	12	0.145	**0.108**	**0.080**	**0.142**	**0.110**	0.148	**0.112**	**0.086**	**0.114**	**0.091**	**0.100**
		24	0.259	0.299	0.261	**0.244**	**0.245**	**0.186**	0.286	**0.198**	**0.221**	**0.180**	**0.195**
		36	0.403	**0.357**	**0.314**	**0.371**	**0.351**	**0.292**	**0.323**	**0.271**	**0.352**	**0.238**	**0.333**
		48	0.479	**0.397**	**0.404**	**0.427**	**0.378**	**0.401**	0.548	**0.389**	**0.463**	**0.323**	**0.421**
	Environment	48	0.444	**0.417**	**0.414**	**0.420**	**0.425**	**0.430**	**0.430**	**0.414**	**0.435**	**0.410**	**0.404**
		96	0.472	**0.444**	**0.393**	0.485	**0.436**	**0.438**	**0.434**	**0.410**	**0.408**	**0.427**	**0.402**
		192	0.463	0.541	0.471	0.499	0.469	**0.411**	0.535	**0.407**	**0.436**	0.471	**0.409**
		336	0.458	0.502	0.470	**0.430**	0.460	**0.454**	0.472	0.460	**0.421**	**0.444**	**0.424**
	Public Health	12	0.904	1.054	1.069	1.121	0.999	1.017	1.087	1.112	1.040	1.102	1.022
		24	1.281	**1.261**	1.290	1.403	**1.192**	**1.264**	1.397	**1.201**	**1.182**	1.310	1.296
		36	1.394	1.408	**1.359**	**1.299**	**1.281**	**1.201**	**1.211**	1.443	**1.317**	**1.284**	**1.346**
		48	1.338	1.470	1.440	1.432	1.600	1.529	1.448	1.438	1.396	1.434	**1.325**
	Security	6	123.7	127.0	127.5	124.6	**122.5**	126.7	**122.6**	127.5	126.7	127.0	127.8
		8	126.6	129.5	129.7	129.2	**123.8**	128.0	126.6	129.5	**125.8**	129.1	127.3
		10	129.6	131.3	129.8	129.9	**124.6**	130.5	**129.5**	131.5	**129.3**	130.6	131.7
		12	127.2	**126.7**	132.7	130.4	127.3	129.7	130.6	131.9	130.8	130.2	130.7
	Social Good	6	0.743	0.757	0.766	0.771	0.826	0.753	0.806	0.766	0.752	0.748	0.788
		8	0.805	0.850	0.875	0.811	0.915	0.821	0.810	0.859	0.860	**0.775**	0.818
		10	0.900	**0.818**	0.934	0.909	0.933	**0.816**	0.908	0.907	**0.859**	0.916	0.909
		12	0.922	**0.884**	0.946	0.967	**0.905**	0.951	**0.878**	0.951	0.946	0.942	**0.882**
	Traffic	6	0.176	0.183	**0.172**	**0.147**	**0.172**	**0.164**	**0.158**	**0.172**	**0.161**	**0.151**	**0.152**
		8	0.186	**0.164**	**0.184**	0.219	**0.182**	**0.159**	**0.162**	**0.184**	**0.162**	**0.174**	**0.168**
		10	0.175	0.204	0.191	0.177	0.205	0.182	0.179	0.191	0.206	**0.172**	0.181
		12	0.212	0.252	0.233	0.219	0.240	0.224	**0.207**	0.233	0.214	**0.203**	0.233

Text Model: Doc2Vec. The following tables report the Doc2Vec-based results, where Doc2Vec serves as a lightweight, non-Transformer text encoder. We include Doc2Vec to verify that the benefits of constrained fusion are not tied to large pretrained language models, and to test whether a simple, distributional text representation is sufficient for CFA to extract complementary signal.

Table 68: Multimodal fusion strategies with **Nonstationary Transformer** (+ **Doc2Vec**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Nonstationary Transformer	Agriculture	6	0.051	0.051	0.052	0.052	0.056	0.053	4.078	0.052	0.056	0.054	0.051
		8	0.068	**0.067**	0.070	**0.068**	**0.068**	0.071	2.467	**0.068**	0.072	0.072	0.072
		10	0.092	**0.090**	**0.091**	**0.085**	0.099	**0.092**	0.628	**0.092**	**0.089**	**0.089**	0.093
		12	0.120	**0.117**	**0.116**	**0.109**	**0.118**	**0.118**	0.722	**0.116**	**0.119**	**0.118**	**0.118**
	Climate	6	1.241	1.291	**1.185**	1.309	**1.162**	**1.236**	**1.237**	1.309	**1.175**	1.293	**1.089**
		8	1.300	1.323	**1.122**	**1.256**	**1.294**	**1.281**	**1.073**	**1.212**	**1.298**	**1.167**	**1.270**
		10	1.211	1.244	1.244	1.301	**1.200**	**1.189**	**1.127**	1.219	1.238	**1.189**	1.221
		12	1.219	1.246	1.232	1.232	1.263	**1.153**	**1.078**	1.255	**1.212**	1.220	**1.149**
	Economy	6	0.017	**0.016**	0.017	0.018	0.017	**0.016**	13.766	0.017	0.017	**0.016**	0.018
		8	0.018	0.018	0.018	0.019	0.020	0.022	6.984	**0.018**	**0.018**	0.021	**0.018**
		10	0.019	0.021	0.020	0.022	**0.018**	0.021	1.125	0.019	0.020	0.020	0.019
		12	0.021	0.022	0.021	0.026	0.022	**0.021**	1.040	**0.020**	**0.020**	**0.021**	**0.020**
	Energy	12	0.107	0.117	**0.104**	0.114	**0.095**	0.111	0.188	**0.101**	0.108	0.111	0.115
		24	0.198	0.234	**0.186**	0.229	**0.197**	0.220	0.627	0.233	**0.198**	**0.196**	0.203
		36	0.280	0.327	0.298	0.301	0.370	0.325	0.974	0.324	0.364	0.338	0.328
		48	0.368	0.451	0.422	**0.366**	0.443	0.455	0.712	0.385	0.401	**0.358**	0.371
	Environment	48	0.419	0.424	0.437	0.467	0.478	0.429	0.464	0.439	0.441	0.441	**0.416**
		96	0.444	0.488	0.497	0.471	0.462	0.453	**0.434**	0.462	0.458	0.460	0.465
		192	0.444	0.486	0.466	0.509	0.446	0.481	0.464	**0.436**	**0.437**	0.459	**0.444**
		336	0.437	0.458	**0.431**	0.500	0.441	0.449	0.514	**0.432**	**0.435**	0.443	0.453
	Public Health	12	0.745	0.887	0.887	0.897	**0.727**	0.890	1.062	0.969	0.843	0.784	0.858
		24	1.137	1.162	**1.103**	1.312	1.153	**1.118**	1.979	1.179	**1.065**	1.216	1.162
		36	1.418	**1.360**	**1.246**	**1.230**	**1.280**	**1.313**	1.535	**1.326**	1.467	1.517	**1.366**
		48	1.364	1.655	1.412	**1.302**	1.633	**1.331**	1.605	1.553	**1.300**	1.482	1.530
	Security	6	103.0	**99.768**	105.2	**101.7**	**101.3**	**101.6**	135.7	**101.7**	**100.6**	**101.7**	**100.3**
		8	105.3	105.7	108.7	105.6	105.6	**104.9**	126.3	**104.3**	105.7	**104.2**	**104.2**
		10	110.2	**108.3**	**109.6**	110.5	**107.6**	**107.6**	120.0	**106.7**	**107.3**	**107.4**	**108.1**
		12	110.8	**109.8**	111.3	**108.1**	**110.0**	**109.1**	113.4	**109.5**	**109.7**	**109.5**	**109.5**
	Social Good	6	0.803	**0.798**	0.835	0.836	**0.784**	**0.761**	4.209	**0.772**	**0.778**	0.887	**0.762**
		8	0.940	**0.921**	**0.859**	0.973	**0.925**	**0.871**	2.671	**0.918**	0.955	**0.878**	**0.868**
		10	1.024	1.092	1.039	**0.934**	**1.004**	**0.993**	1.251	**0.977**	**0.946**	1.028	**0.939**
		12	1.049	1.062	1.091	**1.040**	1.104	1.122	**0.976**	1.107	1.135	1.086	**1.048**
	Traffic	6	0.179	**0.177**	**0.175**	**0.171**	0.184	**0.168**	0.615	0.180	**0.170**	**0.178**	**0.179**
		8	0.187	**0.183**	**0.184**	0.198	0.201	**0.181**	0.523	**0.185**	0.195	**0.181**	**0.186**
		10	0.189	0.190	0.191	**0.184**	0.199	**0.184**	0.220	0.193	**0.185**	0.190	**0.182**
		12	0.251	**0.248**	0.252	0.253	**0.232**	**0.238**	0.251	**0.236**	**0.246**	**0.240**	**0.247**

Table 69: Multimodal fusion strategies with **iTransformer** (+ **Doc2Vec**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
iTransformer	Agriculture	6	0.059	**0.058**	0.060	**0.055**	0.061	0.060	4.716	0.060	0.060	**0.059**	0.060
		8	0.077	**0.076**	0.077	**0.071**	**0.076**	0.078	2.397	**0.077**	**0.076**	**0.076**	0.077
		10	0.098	**0.098**	**0.095**	**0.088**	0.099	0.100	0.906	**0.094**	**0.097**	0.098	0.099
		12	0.127	0.127	0.129	**0.116**	0.130	0.127	0.607	0.129	0.130	**0.126**	0.129
	Climate	6	1.130	1.140	**1.119**	1.144	1.151	**1.114**	1.238	**1.115**	1.148	1.149	1.135
		8	1.193	1.218	1.202	**1.163**	**1.173**	**1.173**	**1.145**	1.204	1.203	**1.192**	**1.179**
		10	1.231	**1.183**	**1.209**	**1.195**	**1.151**	**1.203**	**1.081**	**1.207**	**1.204**	**1.203**	**1.208**
		12	1.184	1.187	1.188	1.194	**1.179**	**1.165**	**1.045**	1.186	1.219	**1.180**	**1.184**
	Economy	6	0.015	**0.015**	**0.015**	0.022	**0.015**	0.015	12.723	**0.015**	0.015	**0.015**	**0.015**
		8	0.015	**0.015**	**0.015**	0.016	**0.015**	0.015	8.123	**0.015**	0.015	0.015	0.016
		10	0.016	**0.015**	**0.016**	0.017	**0.015**	0.016	1.576	**0.016**	**0.015**	**0.015**	**0.016**
		12	0.016	**0.016**	**0.016**	0.018	**0.016**	**0.016**	0.905	**0.016**	**0.016**	**0.016**	**0.016**
	Energy	12	0.116	0.119	0.124	**0.096**	**0.112**	**0.113**	0.206	0.122	0.121	0.124	0.131
		24	0.230	0.230	0.232	**0.214**	**0.224**	0.250	0.834	0.234	**0.226**	0.241	0.243
		36	0.315	**0.309**	**0.315**	**0.314**	**0.305**	0.333	1.312	0.330	0.320	0.318	0.328
		48	0.399	0.428	0.425	0.406	0.495	0.424	0.693	0.434	0.436	0.420	0.422
	Environment	48	0.413	0.427	0.416	0.512	0.425	0.418	0.490	0.422	0.421	0.422	0.421
		96	0.417	0.425	0.422	0.470	**0.415**	**0.417**	0.694	0.429	0.423	0.431	0.419
		192	0.432	0.442	0.446	0.494	**0.429**	**0.425**	0.627	**0.426**	**0.418**	**0.419**	0.436
		336	0.422	0.423	0.424	0.462	**0.419**	0.423	0.985	0.431	**0.418**	**0.416**	0.427
	Public Health	12	0.976	1.011	1.071	**0.939**	0.996	0.990	1.136	1.061	**0.950**	1.017	**0.941**
		24	1.446	1.478	1.451	**1.242**	1.499	**1.438**	1.636	**1.445**	1.473	1.448	**1.441**
		36	1.629	1.655	1.660	**1.379**	1.669	**1.620**	2.037	1.659	1.650	1.633	1.638
		48	1.741	1.747	1.757	**1.518**	1.809	1.780	1.741	1.756	1.768	1.759	1.758
	Security	6	104.7	**104.2**	**103.1**	110.6	**103.4**	**102.2**	139.8	**102.6**	**104.2**	**102.5**	**102.7**
		8	108.8	**105.8**	**105.2**	112.8	**108.1**	**106.1**	141.6	**105.2**	**106.5**	**105.5**	109.2
		10	111.9	**109.8**	**108.1**	114.6	**110.1**	**110.7**	122.7	**108.7**	**110.3**	**109.3**	**108.2**
		12	114.3	**112.6**	**111.5**	117.2	**111.5**	**109.7**	121.3	**110.7**	**111.5**	**109.2**	**111.5**
	Social Good	6	0.821	0.831	0.830	**0.775**	0.852	0.856	4.174	0.831	0.838	0.831	0.835
		8	0.960	**0.948**	**0.954**	**0.943**	**0.937**	0.963	2.762	**0.953**	**0.941**	0.961	**0.955**
		10	1.056	1.064	1.069	**1.001**	**1.054**	1.058	1.084	1.068	1.063	**1.050**	1.061
		12	1.150	**1.145**	1.153	**1.068**	**1.102**	**1.134**	**1.051**	1.153	**1.149**	**1.133**	**1.130**
	Traffic	6	0.182	**0.182**	**0.176**	0.188	0.184	**0.172**	0.458	**0.172**	**0.168**	**0.164**	**0.173**
		8	0.186	0.192	**0.183**	0.195	0.187	0.188	0.789	**0.184**	**0.179**	0.188	**0.183**
		10	0.195	**0.191**	**0.181**	0.196	**0.190**	**0.181**	0.304	**0.181**	**0.184**	**0.184**	**0.190**
		12	0.254	**0.234**	**0.228**	0.256	**0.250**	**0.251**	0.276	**0.226**	**0.225**	**0.226**	**0.242**

Table 70: Multimodal fusion strategies with **Koopa** (+ **Doc2Vec**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	CFA
Koopa	Agriculture	6	0.056	**0.056**	0.056	0.056	2.967	3.376	2.346	0.059	0.062	**0.054**	**0.056**
		8	0.078	0.090	**0.071**	**0.070**	0.177	0.331	0.297	**0.076**	0.083	**0.076**	**0.075**
		10	0.100	0.130	**0.090**	**0.090**	2.205	0.738	0.714	0.101	0.101	**0.091**	**0.100**
		12	0.129	0.133	**0.116**	**0.115**	5.842	2.913	2.581	**0.127**	0.146	**0.116**	0.129
	Climate	6	1.249	1.783	1.263	1.263	1.834	**1.216**	**1.215**	1.254	**1.017**	1.259	**1.243**
		8	1.272	**1.255**	1.277	1.279	**1.143**	**1.091**	**1.088**	1.294	**1.025**	**1.240**	**1.262**
		10	1.249	**1.240**	**1.246**	1.251	**1.195**	**1.054**	**1.054**	**1.245**	**1.046**	**1.227**	**1.244**
		12	1.242	1.244	**1.237**	**1.238**	**1.211**	**1.221**	**1.222**	1.274	**1.057**	**1.238**	**1.231**
	Economy	6	0.017	0.028	0.032	0.033	14.673	14.901	13.798	0.024	0.048	0.020	0.018
		8	0.017	0.020	0.024	0.023	1.001	1.064	1.045	0.027	0.029	0.018	**0.017**
		10	0.018	0.029	0.026	0.025	4.957	2.423	2.443	0.027	0.036	0.019	**0.017**
		12	0.018	0.040	0.025	0.021	14.385	13.308	10.977	0.020	0.047	0.023	**0.018**
	Energy	12	0.108	7.963	0.108	0.108	1.590	0.203	0.210	0.114	0.115	0.108	**0.105**
		24	0.210	0.319	0.220	0.223	4.487	0.446	0.475	0.241	0.220	0.215	0.220
		36	0.306	**0.289**	**0.297**	**0.297**	0.719	0.572	0.673	0.328	0.314	**0.292**	**0.284**
		48	0.404	34.576	0.423	0.416	1.305	0.948	0.954	0.429	**0.401**	**0.384**	0.408
	Environment	48	0.480	95645.1	0.575	1.234	24986.4	0.722	0.802	0.490	0.587	0.921	0.482
		96	0.533	58063.8	1.102	0.865	37111.5	0.980	0.934	0.535	0.757	0.731	**0.524**
		192	0.568	347050.2	0.713	0.736	3030.7	0.649	0.647	0.573	1.251	0.822	**0.567**
		336	0.530	81048.2	0.713	0.577	18262.9	1.021	0.913	**0.529**	0.547	0.613	**0.529**
	Public Health	12	1.035	7.698	**0.955**	**0.961**	3.428	**1.023**	**1.018**	1.198	1.313	**0.941**	**0.952**
		24	1.396	**1.163**	**1.166**	**1.197**	1.859	**1.235**	**1.234**	1.530	**1.391**	**1.154**	1.412
		36	1.624	**1.300**	**1.292**	**1.287**	2.163	1.624	1.686	1.806	**1.394**	**1.256**	1.629
		48	1.733	**1.406**	**1.384**	**1.390**	2.316	1.943	2.020	1.877	**1.442**	**1.372**	**1.724**
	Security	6	104.6	**97.318**	**103.5**	**103.5**	134.4	138.9	139.8	**104.2**	107.2	**103.4**	105.1
		8	109.4	116.9	111.1	111.0	111.0	112.1	112.1	**105.7**	110.2	111.0	**106.6**
		10	108.9	**107.9**	**108.8**	**108.8**	117.8	118.4	118.3	110.1	113.2	109.1	**108.5**
		12	111.0	**102.5**	**110.6**	**110.6**	139.1	137.6	137.4	115.1	114.9	**110.8**	111.2
	Social Good	6	0.852	0.955	**0.800**	**0.800**	3.409	3.506	3.506	**0.848**	**0.787**	0.869	**0.838**
		8	0.922	1.255	**0.893**	**0.892**	0.992	1.000	1.026	0.926	**0.797**	**0.879**	**0.921**
		10	0.991	1.137	**0.964**	**0.966**	1.102	1.231	1.149	**0.971**	**0.912**	**0.886**	0.992
		12	1.083	**1.011**	**0.994**	**0.994**	3.020	2.967	2.947	**1.071**	**0.898**	**0.973**	**1.080**
	Traffic	6	0.231	0.294	**0.220**	**0.221**	0.295	0.506	0.479	**0.215**	**0.218**	**0.215**	**0.202**
		8	0.212	0.216	0.214	0.214	**0.205**	0.219	0.221	0.226	**0.211**	**0.205**	**0.204**
		10	0.219	0.221	0.221	0.220	0.314	0.300	0.333	0.258	**0.200**	**0.210**	**0.209**
		12	0.274	0.321	0.279	0.279	1.013	0.515	0.613	**0.274**	**0.263**	0.278	**0.262**

Table 71: Multimodal fusion strategies with **DLinear** (+ **Doc2Vec**).

TS Model	Dataset	H	Unimodal	**Additive**			**Concat**			**Constrained**			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
DLinear	Agriculture	6	0.094	0.129	0.132	0.120	1.911	2.861	2.080	**0.075**	0.142	0.096	**0.070**
		8	0.324	**0.167**	**0.184**	**0.185**	3.309	3.914	2.666	**0.206**	**0.174**	**0.214**	**0.088**
		10	0.164	0.195	0.205	0.203	0.312	0.280	0.276	**0.151**	**0.147**	0.191	**0.135**
		12	0.217	0.240	0.240	0.240	0.381	0.288	0.289	**0.162**	0.406	**0.178**	**0.164**
	Climate	6	1.140	1.263	1.209	1.198	1.213	1.218	1.227	1.271	**1.054**	**1.087**	**1.087**
		8	1.295	**1.283**	**1.290**	**1.273**	**1.196**	**1.074**	**1.100**	**1.277**	**1.074**	**1.108**	**1.112**
		10	1.155	1.300	1.284	1.268	**1.141**	**1.118**	**1.112**	1.330	**1.112**	1.167	**1.109**
		12	1.175	1.239	1.213	1.182	**1.115**	**1.111**	**1.107**	1.191	**1.100**	**1.137**	**1.096**
	Economy	6	0.095	**0.087**	0.097	0.097	13.039	12.557	12.846	0.107	0.097	**0.046**	**0.023**
		8	0.234	**0.102**	**0.142**	**0.144**	10.613	9.270	10.797	**0.130**	**0.105**	**0.150**	**0.038**
		10	0.086	0.115	0.132	0.130	0.493	0.468	0.482	0.140	**0.038**	0.140	**0.045**
		12	0.109	0.129	0.131	0.129	1.149	0.433	0.396	**0.062**	0.256	**0.092**	**0.054**
	Energy	12	0.116	0.141	0.144	0.132	0.150	0.142	0.143	0.126	**0.113**	0.123	**0.104**
		24	0.222	0.255	0.240	0.252	0.427	0.295	0.289	0.241	0.225	**0.210**	**0.204**
		36	0.300	0.332	0.309	0.320	0.758	0.332	0.341	0.315	0.334	0.300	**0.293**
		48	0.412	0.482	0.472	0.465	0.641	0.447	0.449	0.426	**0.389**	**0.398**	**0.407**
	Environment	48	0.491	0.940	1.113	0.777	0.773	0.592	0.577	0.494	0.833	1.290	0.492
		96	0.568	0.792	0.694	0.577	1.158	0.819	0.764	0.590	1.061	0.978	**0.568**
		192	0.592	0.682	1.314	0.730	0.886	0.782	0.649	0.608	1.252	0.900	0.592
		336	0.538	0.600	**0.523**	**0.533**	0.828	0.555	0.744	0.554	0.646	0.784	**0.537**
	Public Health	12	1.357	**1.336**	1.428	1.362	1.438	1.573	1.618	1.581	**1.350**	**1.349**	**1.249**
		24	1.593	**1.582**	1.671	1.620	1.707	1.775	1.720	1.624	**1.483**	**1.546**	**1.500**
		36	1.636	1.647	**1.531**	**1.508**	1.664	1.670	1.642	1.691	**1.596**	**1.617**	**1.595**
		48	1.683	1.708	**1.627**	**1.591**	1.864	1.745	1.753	1.734	1.686	**1.678**	**1.672**
	Security	6	104.3	104.5	104.7	104.6	167.4	165.1	165.5	105.6	104.4	104.6	104.8
		8	109.2	**108.1**	**107.6**	**107.8**	150.9	146.2	145.5	110.3	**106.5**	**108.4**	**108.9**
		10	110.5	111.6	**109.7**	**109.9**	111.4	**108.4**	111.0	**110.5**	110.9	**110.0**	**109.8**
		12	111.8	112.2	111.8	112.1	113.3	112.8	113.2	113.4	**111.3**	**111.5**	**111.6**
	Social Good	6	0.847	**0.814**	**0.828**	**0.818**	3.013	1.549	1.576	0.904	**0.821**	**0.786**	**0.785**
		8	0.878	0.912	0.897	0.897	2.101	1.804	1.926	0.889	**0.862**	**0.863**	**0.869**
		10	0.949	0.983	1.022	1.001	**0.944**	0.958	**0.936**	0.977	0.982	0.972	0.958
		12	1.015	**1.000**	1.037	**0.997**	**1.001**	**1.012**	**0.998**	**1.015**	**1.004**	1.018	**1.002**
	Traffic	6	0.252	0.262	0.299	0.261	0.472	0.507	0.461	0.296	0.345	**0.235**	**0.224**
		8	0.328	**0.291**	**0.325**	**0.301**	0.549	0.867	0.618	**0.268**	**0.292**	**0.305**	**0.223**
		10	0.238	0.267	0.315	0.289	0.349	0.270	0.263	**0.227**	0.259	0.268	**0.219**
		12	0.288	0.308	0.334	0.316	0.365	0.407	**0.277**	**0.281**	0.309	0.306	**0.262**

Table 72: Multimodal fusion strategies with **PatchTST** (+ **Doc2Vec**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
PatchTST	Agriculture	6	0.060	**0.060**	**0.058**	**0.059**	**0.060**	**0.059**	2.663	0.060	**0.058**	0.061	**0.057**
		8	0.080	**0.080**	**0.078**	**0.075**	**0.080**	**0.079**	2.320	**0.078**	**0.077**	**0.079**	**0.079**
		10	0.099	0.100	0.101	**0.093**	0.100	0.101	0.502	**0.099**	0.101	0.101	0.099
		12	0.129	0.129	0.129	**0.119**	0.129	0.130	0.589	0.129	**0.128**	0.130	**0.126**
	Climate	6	1.255	**1.237**	**1.238**	**1.238**	**1.237**	**1.238**	1.283	**1.238**	**1.205**	**1.251**	**1.234**
		8	1.261	**1.248**	**1.227**	**1.249**	**1.248**	**1.258**	**1.143**	**1.226**	**1.252**	**1.255**	**1.243**
		10	1.280	**1.263**	**1.261**	**1.263**	**1.263**	**1.242**	**1.104**	**1.260**	**1.246**	**1.277**	**1.267**
		12	1.238	1.245	1.251	1.253	1.245	1.254	**1.090**	1.251	1.260	1.246	1.248
	Economy	6	0.016	0.016	0.017	0.017	0.016	0.017	17.750	0.017	0.016	0.017	0.017
		8	0.017	**0.017**	**0.017**	0.020	**0.017**	**0.017**	9.522	0.018	**0.016**	**0.017**	**0.017**
		10	0.017	**0.017**	**0.016**	0.019	**0.017**	**0.017**	1.590	**0.016**	0.017	0.018	0.018
		12	0.018	**0.017**	**0.017**	0.020	**0.017**	0.018	1.435	**0.017**	**0.018**	**0.017**	**0.017**
	Energy	12	0.109	0.111	0.114	0.110	0.111	0.113	0.222	0.117	0.112	**0.109**	0.116
		24	0.221	**0.211**	0.222	0.225	**0.211**	**0.216**	0.606	0.232	0.231	0.228	0.231
		36	0.316	**0.313**	0.326	0.318	**0.313**	0.329	1.446	0.326	0.330	0.325	**0.314**
		48	0.401	0.406	0.444	0.421	0.406	0.426	0.575	0.445	0.439	0.441	0.429
	Environment	48	0.465	**0.463**	0.518	0.500	**0.463**	0.470	0.558	0.500	**0.462**	**0.462**	**0.462**
		96	0.494	0.497	0.501	0.795	0.497	**0.493**	0.639	0.522	0.507	0.509	0.522
		192	0.543	0.545	**0.517**	0.603	0.545	**0.541**	0.837	**0.536**	0.547	**0.530**	0.562
		336	0.503	0.515	0.514	0.560	0.515	0.530	0.844	0.515	0.510	**0.493**	0.525
	Public Health	12	0.925	**0.876**	0.928	**0.838**	**0.876**	0.949	**0.913**	0.949	1.034	**0.906**	**0.896**
		24	1.386	**1.359**	1.390	**1.267**	**1.359**	**1.265**	1.622	1.386	**1.381**	1.390	1.425
		36	1.612	**1.600**	1.630	**1.389**	**1.600**	**1.593**	2.223	1.637	1.614	1.623	**1.612**
		48	1.749	1.755	**1.737**	**1.567**	1.755	**1.736**	**1.747**	**1.732**	1.761	1.759	1.771
	Security	6	103.8	104.7	**102.8**	105.7	104.7	**103.3**	145.1	**103.3**	104.0	104.2	104.6
		8	107.6	**107.2**	**105.9**	110.7	**107.2**	**106.4**	135.5	**106.5**	**106.7**	**107.1**	**107.6**
		10	111.5	112.0	**108.2**	**109.2**	112.0	**108.4**	120.1	**108.4**	**110.6**	**107.9**	**111.2**
		12	110.9	111.5	**110.8**	111.7	111.5	111.1	120.7	**110.8**	113.3	111.8	112.1
	Social Good	6	0.806	**0.794**	**0.795**	0.818	**0.794**	**0.796**	3.828	**0.794**	**0.798**	**0.794**	**0.795**
		8	0.905	**0.900**	**0.885**	**0.865**	**0.900**	0.907	2.397	**0.884**	**0.904**	**0.901**	**0.890**
		10	1.008	1.028	1.046	1.017	1.028	1.050	1.062	**1.000**	1.023	1.032	1.039
		12	1.131	**1.080**	**1.090**	**0.970**	**1.080**	**1.076**	**1.053**	**1.091**	**1.064**	**1.107**	**1.083**
	Traffic	6	0.177	**0.174**	0.180	0.177	**0.174**	0.179	0.481	**0.169**	0.186	**0.172**	0.186
		8	0.182	0.186	**0.179**	0.189	0.186	**0.181**	0.299	0.185	0.185	**0.179**	**0.181**
		10	0.193	**0.185**	**0.187**	0.198	**0.185**	**0.192**	0.214	**0.187**	**0.183**	**0.183**	0.194
		12	0.237	0.249	**0.234**	0.243	0.249	0.247	0.321	**0.236**	0.246	**0.225**	0.239

Table 73: Multimodal fusion strategies with **FiLM** (+ **Doc2Vec**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
FiLM	Agriculture	6	0.060	0.088	0.061	**0.059**	7.138	0.062	2.962	0.063	0.062	0.061	0.061
		8	0.082	0.311	**0.082**	**0.076**	5.513	0.084	1.729	**0.080**	**0.079**	**0.079**	**0.079**
		10	0.104	0.168	0.104	**0.100**	0.672	0.104	0.684	**0.104**	0.105	**0.102**	**0.103**
		12	0.137	1.725	**0.133**	**0.124**	0.317	**0.137**	0.551	**0.134**	**0.136**	**0.135**	**0.135**
	Climate	6	1.354	**1.254**	**1.268**	**1.256**	1.537	**1.272**	**1.284**	**1.250**	**1.244**	**1.234**	**1.300**
		8	1.279	**1.271**	**1.278**	**1.266**	**1.055**	1.281	**1.128**	1.295	**1.273**	**1.277**	**1.266**
		10	1.282	2.865	1.296	**1.278**	1.666	1.290	**1.095**	**1.269**	1.285	**1.270**	**1.271**
		12	1.270	2.392	1.279	1.285	1.687	1.286	**1.101**	**1.269**	**1.267**	1.278	**1.266**
	Economy	6	0.018	0.042	0.021	0.041	23.612	0.018	21.375	**0.018**	0.019	**0.017**	0.018
		8	0.019	0.109	**0.018**	0.019	11.206	0.019	11.501	**0.017**	**0.018**	**0.017**	**0.017**
		10	0.019	0.083	**0.018**	0.022	0.137	0.020	1.474	**0.018**	**0.018**	**0.017**	**0.018**
		12	0.019	0.508	0.019	0.040	0.036	0.020	1.632	**0.018**	**0.018**	**0.018**	**0.018**
	Energy	12	0.116	13.430	**0.114**	0.128	0.353	0.150	0.280	**0.103**	**0.105**	**0.104**	**0.104**
		24	0.221	0.326	0.239	**0.217**	0.673	0.246	0.810	**0.209**	0.226	0.231	**0.217**
		36	0.320	44.538	0.326	0.321	1.590	0.348	1.401	**0.300**	**0.303**	0.329	**0.313**
		48	0.445	0.623	**0.437**	**0.428**	0.680	0.459	0.648	**0.432**	**0.421**	**0.423**	**0.425**
	Environment	48	0.491	65958.3	**0.486**	0.638	0.652	0.533	0.566	**0.490**	0.516	0.493	**0.488**
		96	0.545	247802.2	**0.545**	1.312	0.695	0.635	0.775	0.549	0.568	0.546	**0.542**
		192	0.572	284870.7	0.576	0.855	0.602	0.576	0.716	**0.570**	0.601	0.573	**0.570**
		336	0.530	7.076	0.564	0.631	692.9	0.532	0.771	**0.529**	0.537	0.531	**0.528**
	Public Health	12	1.159	30.068	1.176	**0.983**	1.950	1.305	**1.131**	**1.124**	**1.145**	**1.131**	**1.129**
		24	1.491	**1.428**	1.510	**1.338**	2.024	1.567	1.745	**1.431**	**1.485**	1.505	**1.458**
		36	1.612	1.806	1.691	1.695	2.242	1.660	2.087	1.661	1.663	1.652	1.669
		48	1.705	2.023	1.772	1.866	1.987	1.760	1.873	1.716	1.768	1.718	1.738
	Security	6	127.3	**97.900**	**102.1**	**101.1**	214.1	**103.2**	186.0	**102.8**	**102.1**	**104.4**	**107.0**
		8	113.8	116.9	**107.9**	116.6	148.7	**107.0**	160.8	**112.1**	**104.1**	**106.8**	**105.1**
		10	117.0	132.9	**109.9**	133.6	**99.472**	**108.9**	**109.8**	**109.5**	**108.8**	**110.2**	**115.2**
		12	119.0	**106.4**	**109.9**	**108.8**	**104.0**	**112.0**	**111.0**	120.5	**109.5**	**112.0**	**112.8**
	Social Good	6	0.921	1.596	**0.834**	**0.828**	4.119	**0.871**	3.622	**0.829**	**0.847**	**0.831**	**0.820**
		8	1.053	12.330	**0.988**	**1.050**	2.416	**1.010**	2.589	**1.014**	**0.934**	**0.963**	**0.963**
		10	1.106	1.547	1.122	1.198	5.796	**1.092**	**1.095**	**1.014**	1.113	**1.082**	1.107
		12	1.207	8.133	**1.110**	**1.104**	3.560	**1.193**	**1.088**	1.227	**1.201**	**1.138**	**1.164**
	Traffic	6	0.228	0.276	0.238	0.249	1.073	0.236	0.440	0.240	0.234	0.231	0.242
		8	0.223	0.224	**0.220**	**0.221**	0.319	0.230	0.469	0.232	**0.213**	**0.221**	0.234
		10	0.216	0.226	0.217	**0.216**	0.413	0.219	0.407	0.238	**0.214**	0.217	**0.215**
		12	0.253	5.092	0.259	0.267	0.687	0.264	0.386	0.283	**0.244**	0.274	**0.250**

Table 74: Multimodal fusion strategies with **TiDE** (+ **Doc2Vec**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
TiDE	Agriculture	6	0.072	**0.070**	0.086	**0.070**	3.204	**0.069**	3.675	**0.060**	**0.063**	**0.061**	**0.060**
		8	0.087	**0.084**	0.090	0.093	1.532	0.091	1.582	**0.083**	**0.081**	**0.082**	**0.081**
		10	0.112	0.266	**0.112**	0.114	0.168	0.121	0.461	**0.103**	**0.104**	**0.103**	**0.103**
		12	0.151	0.496	**0.146**	**0.131**	1.262	**0.150**	1.014	**0.135**	**0.134**	**0.133**	**0.134**
	Climate	6	1.443	1.533	1.553	1.528	1.573	**1.433**	**1.409**	**1.259**	**1.235**	**1.238**	**1.261**
		8	1.506	**1.448**	**1.384**	**1.461**	**1.111**	1.546	**1.138**	**1.262**	**1.278**	**1.250**	**1.366**
		10	1.397	1.558	1.402	1.423	1.417	1.546	**1.177**	**1.279**	**1.270**	**1.258**	**1.254**
		12	1.468	1.518	**1.422**	**1.390**	**1.251**	1.472	**1.132**	**1.255**	**1.274**	**1.262**	**1.269**
	Economy	6	0.033	0.046	0.039	0.048	20.458	0.050	21.635	**0.019**	**0.017**	**0.016**	**0.018**
		8	0.039	0.046	**0.038**	**0.039**	11.799	**0.031**	11.915	**0.018**	**0.018**	**0.017**	**0.017**
		10	0.029	0.050	0.032	0.038	0.148	0.040	1.679	**0.018**	**0.017**	**0.018**	**0.018**
		12	0.033	0.042	**0.031**	0.034	1.603	0.038	1.593	**0.018**	**0.018**	**0.018**	**0.017**
	Energy	12	0.135	4.723	0.138	**0.134**	0.842	0.135	0.210	**0.106**	**0.102**	**0.105**	**0.106**
		24	0.242	0.435	**0.238**	**0.236**	0.829	0.249	0.818	**0.218**	**0.219**	**0.211**	**0.204**
		36	0.326	53.277	0.332	**0.318**	21.779	0.335	1.655	**0.292**	**0.302**	**0.289**	**0.295**
		48	0.444	0.530	**0.437**	**0.416**	0.760	**0.441**	0.793	**0.406**	**0.408**	**0.414**	**0.403**
	Environment	48	0.484	1.118	**0.483**	1.019	0.804	**0.483**	0.781	**0.483**	**0.483**	0.484	**0.482**
		96	0.543	1.341	**0.543**	1.262	0.661	**0.539**	0.668	**0.541**	**0.537**	**0.542**	**0.543**
		192	0.576	151.7	0.577	0.805	11910.0	0.577	0.757	0.577	0.576	0.578	0.576
		336	0.533	6258.2	0.533	0.539	2568.8	**0.532**	0.660	0.533	0.533	0.535	**0.533**
	Public Health	12	1.323	2.924	**1.314**	**1.156**	2.002	**1.279**	**1.307**	**1.107**	**1.078**	**1.083**	**1.089**
		24	1.537	2.307	**1.508**	**1.481**	1.799	1.606	1.827	**1.450**	**1.478**	**1.439**	**1.426**
		36	1.676	10.500	**1.669**	**1.600**	12.984	1.702	2.238	**1.637**	**1.638**	**1.609**	**1.623**
		48	1.772	2.218	1.776	**1.747**	1.847	**1.768**	1.956	**1.715**	1.772	**1.722**	**1.727**
	Security	6	146.5	**123.0**	**134.9**	**123.4**	197.7	**122.0**	188.9	**104.4**	**106.6**	**107.2**	**108.1**
		8	129.5	133.4	132.5	133.7	152.8	**129.0**	154.9	**107.9**	**108.5**	**112.4**	**108.5**
		10	132.2	138.2	135.1	**132.1**	**99.922**	135.3	**117.1**	**112.6**	**110.1**	**113.5**	**112.7**
		12	145.2	**142.5**	**139.1**	**134.4**	**103.0**	**142.3**	**120.1**	**112.5**	**112.8**	**112.8**	**111.8**
	Social Good	6	0.968	**0.914**	1.043	**0.916**	4.189	**0.915**	4.017	**0.836**	**0.884**	**0.862**	**0.825**
		8	1.140	**1.078**	**1.059**	**1.025**	2.249	**1.057**	2.311	**0.952**	**0.943**	**0.952**	**0.950**
		10	1.127	2.480	1.184	1.187	3.021	1.264	**0.986**	**1.057**	**1.062**	**1.064**	**1.078**
		12	1.351	6.833	**1.185**	**1.266**	1.430	**1.216**	**1.060**	**1.192**	**1.160**	**1.156**	**1.142**
	Traffic	6	0.298	0.303	**0.286**	0.308	0.730	0.316	0.763	**0.236**	**0.235**	**0.237**	**0.233**
		8	0.303	**0.300**	**0.277**	**0.298**	0.351	**0.284**	0.391	**0.232**	**0.229**	**0.233**	**0.225**
		10	0.248	0.861	**0.245**	0.297	1.311	0.296	0.475	**0.223**	**0.231**	**0.225**	**0.228**
		12	0.319	1.090	**0.308**	0.324	0.496	0.334	**0.316**	**0.288**	**0.288**	**0.284**	**0.290**

Table 75: Multimodal fusion strategies with **FEDformer** (+ **Doc2Vec**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
FEDformer	Agriculture	6	0.055	0.058	0.060	**0.054**	0.063	0.060	3.212	0.058	0.057	0.062	0.061
		8	0.072	0.076	**0.069**	**0.070**	0.080	0.073	2.878	**0.069**	0.075	0.073	**0.068**
		10	0.086	0.088	0.094	0.094	0.101	0.087	0.787	0.095	0.092	0.088	0.088
		12	0.112	0.128	0.126	0.118	0.128	0.119	0.642	0.121	0.125	0.114	0.117
	Climate	6	1.084	1.093	1.129	**1.058**	**1.055**	1.084	1.191	**1.069**	1.103	**1.083**	**1.081**
		8	1.097	**1.060**	**1.048**	**1.065**	**1.034**	**1.064**	**0.965**	**1.062**	**1.056**	**1.063**	**1.059**
		10	1.113	**1.108**	**1.097**	**1.102**	**1.049**	**1.081**	**0.926**	**1.099**	**1.077**	**1.070**	**1.069**
		12	1.109	**1.076**	**1.104**	**1.095**	**1.092**	**1.090**	**0.913**	**1.107**	1.111	**1.091**	**1.071**
	Economy	6	0.038	**0.036**	**0.027**	0.040	**0.037**	0.039	9.961	**0.030**	0.046	**0.034**	**0.038**
		8	0.050	**0.047**	**0.045**	0.053	**0.028**	**0.041**	6.877	**0.027**	0.051	0.050	**0.043**
		10	0.039	0.042	**0.034**	0.047	0.043	**0.035**	1.150	**0.035**	**0.031**	**0.036**	0.042
		12	0.051	**0.033**	**0.048**	0.052	**0.041**	**0.035**	1.164	**0.032**	**0.037**	**0.036**	**0.043**
	Energy	12	0.097	0.105	**0.092**	**0.095**	0.114	**0.093**	0.189	**0.093**	**0.096**	**0.092**	**0.093**
		24	0.177	0.242	0.190	**0.176**	0.193	0.180	0.868	0.198	0.187	0.181	0.186
		36	0.257	0.270	0.259	**0.247**	0.285	0.261	1.438	**0.256**	**0.253**	0.274	0.264
		48	0.365	0.376	0.369	0.378	0.500	0.382	0.861	**0.362**	0.380	**0.363**	0.384
	Environment	48	0.461	0.478	0.466	0.518	0.493	**0.448**	0.662	0.503	0.608	0.510	0.470
		96	0.480	0.563	0.514	0.708	0.497	**0.470**	**0.463**	0.543	0.505	0.523	0.493
		192	0.484	0.508	0.526	0.585	0.569	0.518	0.691	0.511	0.495	0.514	0.505
		336	0.470	0.485	**0.464**	0.535	**0.468**	0.482	0.697	**0.465**	0.481	0.486	0.485
	Public Health	12	1.070	1.110	1.090	**1.062**	1.129	1.099	**1.025**	1.083	1.088	1.078	1.108
		24	1.311	1.412	1.398	1.415	1.406	1.383	1.480	1.346	1.353	**1.305**	1.402
		36	1.557	**1.550**	**1.544**	**1.536**	**1.489**	**1.536**	1.961	**1.502**	**1.500**	**1.495**	**1.466**
		48	1.558	1.600	1.575	**1.541**	1.592	**1.497**	1.604	1.604	**1.513**	**1.524**	**1.519**
	Security	6	105.9	109.3	106.7	113.2	106.1	**105.0**	161.1	106.6	**105.4**	108.7	106.9
		8	107.9	**107.1**	**107.3**	109.3	110.2	**105.4**	141.2	**107.2**	110.5	109.8	110.0
		10	113.7	**112.1**	**111.7**	114.6	**111.5**	115.2	117.5	**111.7**	**112.2**	**109.3**	114.4
		12	117.4	118.5	**114.5**	117.6	**114.1**	122.6	118.5	**114.5**	**113.6**	**111.0**	**114.1**
	Social Good	6	0.905	**0.844**	**0.841**	**0.806**	**0.891**	**0.860**	2.253	**0.817**	**0.815**	**0.867**	**0.859**
		8	0.890	**0.850**	**0.850**	**0.863**	**0.856**	**0.837**	2.710	**0.850**	**0.812**	0.895	**0.865**
		10	0.948	**0.924**	**0.902**	**0.900**	1.091	**0.894**	1.080	**0.902**	**0.884**	0.960	**0.900**
		12	1.043	**1.006**	**0.982**	**1.003**	1.092	**0.960**	1.066	**0.980**	**0.962**	**0.985**	**0.964**
	Traffic	6	0.152	**0.152**	**0.152**	**0.151**	**0.145**	**0.147**	0.653	**0.152**	0.152	**0.150**	0.152
		8	0.155	0.160	0.157	**0.151**	**0.152**	0.156	0.347	0.156	**0.153**	0.158	**0.155**
		10	0.166	**0.164**	**0.162**	**0.165**	**0.147**	**0.163**	0.206	**0.163**	0.168	**0.164**	**0.162**
		12	0.221	0.243	0.229	0.222	**0.212**	0.225	0.231	0.227	**0.217**	**0.211**	**0.219**

Table 76: Multimodal fusion strategies with **Autoformer** (+ **Doc2Vec**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Autoformer	Agriculture	6	0.071	**0.070**	**0.066**	**0.065**	**0.068**	**0.061**	3.357	**0.063**	**0.065**	**0.065**	**0.065**
		8	0.088	0.089	**0.084**	**0.083**	**0.084**	**0.083**	1.849	**0.079**	0.090	**0.074**	0.092
		10	0.095	0.109	0.107	0.104	0.112	0.098	1.030	0.110	0.103	0.098	0.108
		12	0.136	**0.130**	**0.128**	**0.133**	0.144	**0.133**	0.637	**0.127**	**0.128**	**0.126**	**0.120**
	Climate	6	1.241	**1.204**	**1.235**	**1.224**	**1.173**	**1.119**	1.297	1.260	**1.220**	**1.165**	**1.221**
		8	1.201	1.215	1.204	**1.156**	1.247	**1.157**	**1.008**	**1.201**	**1.170**	1.223	**1.147**
		10	1.211	1.238	**1.196**	**1.188**	**1.154**	1.215	**1.082**	**1.195**	**1.151**	**1.146**	1.277
		12	1.183	**1.165**	1.189	1.185	1.217	**1.171**	**0.970**	1.193	**1.158**	**1.125**	1.188
	Economy	6	0.058	0.059	**0.051**	**0.051**	0.072	0.061	13.506	**0.053**	0.058	0.068	**0.042**
		8	0.063	0.067	**0.062**	0.069	0.063	**0.055**	7.793	**0.047**	**0.052**	**0.055**	0.067
		10	0.061	0.069	**0.055**	**0.045**	0.074	**0.039**	1.772	**0.054**	0.062	0.070	**0.047**
		12	0.055	**0.049**	**0.051**	0.080	**0.049**	**0.032**	1.602	**0.043**	**0.047**	**0.053**	0.059
	Energy	12	0.128	0.179	0.147	0.167	0.215	0.132	0.361	0.140	0.170	0.186	0.165
		24	0.300	0.331	0.337	0.301	0.328	0.307	0.888	0.316	0.324	**0.299**	**0.288**
		36	0.368	0.373	0.399	0.410	0.381	**0.368**	1.497	0.380	**0.366**	**0.367**	0.395
		48	0.494	**0.476**	**0.484**	0.496	**0.485**	**0.478**	0.759	**0.463**	**0.481**	**0.473**	**0.488**
	Environment	48	0.523	0.596	0.559	0.827	0.618	0.572	0.558	**0.523**	0.615	0.554	0.540
		96	0.541	0.718	0.756	0.620	0.599	0.563	1.372	0.746	0.595	0.649	0.577
		192	0.568	0.583	0.624	0.896	0.613	0.658	0.915	0.694	0.950	0.889	0.634
		336	0.514	0.555	0.537	0.673	0.543	0.605	0.723	0.561	0.609	0.566	0.568
	Public Health	12	1.506	1.579	1.748	1.558	1.708	**1.389**	1.596	1.538	1.529	1.513	1.603
		24	1.882	2.028	2.024	1.890	1.895	1.950	**1.610**	**1.827**	**1.765**	1.899	**1.870**
		36	1.867	1.907	1.983	1.876	2.201	1.910	**1.833**	1.877	**1.863**	**1.826**	**1.852**
		48	1.953	**1.892**	2.059	**1.850**	**1.906**	**1.852**	**1.664**	**1.925**	**1.820**	**1.867**	**1.921**
	Security	6	105.8	108.2	108.3	**105.5**	**104.4**	109.0	154.2	108.0	108.0	109.3	109.8
		8	110.5	**108.7**	110.9	111.2	111.0	111.6	134.2	**108.3**	**106.8**	**107.4**	114.7
		10	115.2	**112.8**	115.5	**115.0**	**112.5**	**112.7**	**114.4**	115.5	**111.5**	116.4	**114.6**
		12	117.2	**116.9**	**115.4**	**115.3**	**114.0**	118.3	118.6	**115.4**	**111.6**	**116.8**	**113.1**
	Social Good	6	0.896	**0.812**	**0.854**	**0.847**	**0.819**	0.910	4.220	**0.837**	**0.857**	**0.860**	**0.835**
		8	0.972	0.983	**0.957**	1.022	1.010	**0.937**	2.715	0.992	1.033	**0.950**	0.988
		10	0.983	1.009	1.075	1.042	1.105	0.989	1.034	1.006	1.041	0.999	1.037
		12	1.092	1.122	**1.067**	1.125	1.194	1.136	1.135	1.104	1.190	**1.089**	**1.059**
	Traffic	6	0.173	0.192	**0.170**	**0.158**	**0.167**	**0.164**	0.520	**0.167**	**0.170**	0.174	0.196
		8	0.186	0.188	0.198	0.200	0.245	**0.180**	0.429	0.192	0.195	0.194	0.187
		10	0.192	**0.191**	**0.185**	0.210	0.215	**0.171**	0.197	0.195	**0.189**	0.208	**0.185**
		12	0.241	0.260	**0.234**	**0.238**	**0.233**	**0.227**	0.287	**0.233**	0.250	**0.235**	**0.224**

Table 77: Multimodal fusion strategies with **Crossformer** (+ **Doc2Vec**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Crossformer	Agriculture	6	0.152	**0.117**	0.195	**0.151**	**0.130**	0.226	0.192	0.155	**0.118**	**0.139**	0.173
		8	0.198	0.248	0.281	**0.149**	0.743	0.295	0.239	0.283	0.261	0.254	**0.167**
		10	0.265	**0.215**	**0.247**	0.346	**0.261**	0.395	0.378	0.268	0.299	**0.192**	**0.251**
		12	0.380	**0.357**	**0.363**	0.401	**0.307**	0.509	0.538	0.396	**0.282**	**0.326**	0.459
	Climate	6	1.063	**1.053**	**1.027**	**1.049**	**1.024**	**1.053**	1.081	1.093	1.067	**1.024**	**1.050**
		8	1.079	1.109	1.081	1.115	1.136	**1.072**	1.094	**1.060**	1.088	1.081	1.079
		10	1.079	1.097	**1.075**	1.105	1.084	1.097	1.080	1.105	1.085	1.101	1.101
		12	1.099	**1.096**	1.111	1.116	1.129	**1.090**	**1.080**	**1.072**	**1.094**	**1.090**	1.106
	Economy	6	0.477	**0.077**	**0.409**	**0.229**	**0.353**	0.697	0.519	**0.218**	**0.247**	**0.138**	**0.180**
		8	0.366	**0.296**	**0.162**	**0.179**	5.881	0.666	**0.326**	**0.180**	**0.167**	**0.255**	0.515
		10	0.374	0.797	0.688	0.588	**0.347**	0.764	1.015	**0.146**	**0.364**	0.441	**0.251**
		12	0.722	**0.581**	**0.568**	1.073	**0.559**	**0.648**	1.065	**0.376**	**0.295**	**0.561**	**0.168**
	Energy	12	0.130	0.131	0.151	0.171	0.177	0.151	0.162	0.151	0.132	0.148	**0.114**
		24	0.256	**0.238**	**0.238**	0.265	0.451	0.288	0.288	0.283	0.280	0.265	**0.249**
		36	0.344	**0.336**	0.359	**0.340**	0.346	0.351	0.351	**0.335**	**0.344**	**0.332**	0.355
		48	0.440	0.449	**0.433**	**0.417**	**0.427**	0.466	0.470	0.440	0.453	0.459	**0.428**
	Environment	48	0.492	0.580	0.511	0.573	0.549	0.504	0.571	0.499	0.581	0.531	0.529
		96	0.542	**0.530**	0.639	0.751	0.603	0.591	0.573	0.584	0.637	0.606	**0.533**
		192	0.521	0.590	0.649	0.686	0.658	0.619	0.608	0.588	0.616	0.591	0.584
		336	0.528	0.540	0.593	0.662	0.530	0.558	0.619	0.587	0.587	0.577	0.543
	Public Health	12	1.172	1.180	**1.106**	**1.132**	1.247	**1.136**	**1.126**	**1.136**	**1.132**	**1.044**	**1.023**
		24	1.356	1.377	**1.350**	1.359	1.686	1.444	1.463	**1.354**	**1.337**	**1.315**	**1.349**
		36	1.391	1.392	**1.389**	**1.286**	**1.362**	1.463	1.433	1.405	**1.388**	**1.292**	**1.366**
		48	1.480	**1.438**	**1.452**	1.523	1.504	**1.432**	1.540	**1.471**	1.483	**1.472**	**1.427**
	Security	6	120.5	120.7	121.4	**117.5**	**120.3**	120.6	121.7	**120.3**	**120.1**	**119.7**	**119.4**
		8	121.8	124.1	124.9	124.6	133.0	126.9	126.9	123.3	121.8	122.8	122.0
		10	124.1	125.8	125.6	125.6	124.2	125.4	125.2	126.0	124.5	125.9	**122.4**
		12	127.2	**121.3**	128.6	128.3	128.5	**125.1**	127.8	129.2	**124.9**	128.3	**126.0**
	Social Good	6	0.719	0.729	0.738	0.745	0.742	0.730	0.724	0.742	0.737	0.754	0.733
		8	0.817	0.819	0.817	**0.800**	1.472	**0.795**	0.821	0.832	0.821	**0.812**	**0.813**
		10	0.879	0.902	**0.851**	**0.850**	**0.875**	**0.863**	**0.872**	0.880	**0.867**	**0.869**	0.883
		12	0.928	0.940	**0.926**	0.931	0.943	**0.911**	**0.915**	0.948	**0.900**	**0.912**	0.929
	Traffic	6	0.231	**0.217**	**0.207**	**0.212**	**0.215**	**0.216**	**0.220**	**0.222**	**0.229**	**0.204**	**0.209**
		8	0.210	0.233	0.228	0.219	0.324	0.220	**0.201**	**0.210**	0.213	0.222	0.229
		10	0.220	**0.219**	0.223	0.225	0.224	**0.215**	**0.208**	**0.212**	**0.215**	0.222	**0.217**
		12	0.243	0.250	0.253	0.250	0.269	0.245	**0.243**	0.247	**0.243**	0.248	0.256

Table 78: Multimodal fusion strategies with **Reformer** (+ **Doc2Vec**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Reformer	Agriculture	6	0.189	**0.183**	0.277	**0.181**	0.205	**0.140**	0.322	0.265	**0.181**	0.199	**0.183**
		8	0.217	0.275	**0.215**	**0.173**	0.377	0.235	0.417	0.265	0.295	**0.197**	0.383
		10	0.489	**0.419**	**0.471**	**0.273**	**0.408**	**0.332**	0.732	**0.371**	**0.294**	0.502	**0.341**
		12	0.414	0.585	**0.333**	**0.366**	0.565	0.618	0.601	**0.349**	**0.390**	**0.259**	**0.406**
	Climate	6	0.983	1.013	1.014	1.045	1.007	1.065	**0.933**	1.004	1.093	**0.974**	1.054
		8	1.083	**1.046**	1.105	**1.044**	**1.073**	**1.051**	**0.946**	1.097	**1.065**	**1.078**	**1.042**
		10	1.096	**1.047**	**1.080**	1.112	1.098	**1.069**	**0.907**	**1.075**	1.102	1.113	**1.073**
		12	1.077	**1.046**	1.107	**1.068**	1.121	1.146	**1.052**	1.093	**1.041**	1.100	**1.063**
	Economy	6	0.268	0.332	0.337	0.377	0.643	0.316	0.649	**0.175**	0.302	**0.199**	0.344
		8	0.422	**0.213**	**0.096**	0.536	**0.379**	0.709	1.053	**0.340**	**0.221**	**0.326**	**0.260**
		10	0.447	0.703	0.834	0.531	1.110	0.817	2.016	0.615	**0.441**	0.633	0.747
		12	0.367	1.166	**0.300**	**0.280**	1.543	1.564	0.943	0.435	0.922	0.458	0.381
	Energy	12	0.267	**0.201**	**0.156**	**0.209**	**0.205**	**0.200**	**0.145**	**0.167**	**0.223**	**0.197**	**0.219**
		24	0.436	**0.410**	0.440	**0.408**	**0.317**	**0.383**	**0.333**	**0.401**	**0.401**	**0.372**	**0.400**
		36	0.503	**0.462**	**0.480**	**0.462**	**0.370**	**0.483**	**0.470**	**0.389**	**0.481**	**0.436**	**0.425**
		48	0.600	**0.557**	**0.527**	**0.513**	0.640	**0.536**	**0.583**	**0.510**	**0.488**	**0.523**	**0.518**
	Environment	48	0.411	0.533	0.466	0.454	**0.403**	0.462	0.561	0.463	0.445	0.453	0.453
		96	0.472	0.575	0.497	0.475	0.558	**0.438**	0.686	0.565	0.492	**0.438**	**0.450**
		192	0.437	0.567	0.468	0.485	0.544	0.457	0.709	0.453	0.485	0.456	0.457
		336	0.446	0.468	**0.434**	0.510	0.576	0.458	0.575	0.470	0.446	0.466	0.507
	Public Health	12	1.176	**0.931**	1.251	**1.098**	**1.015**	**1.094**	**1.148**	**1.107**	**1.175**	1.188	**1.086**
		24	1.272	1.341	**1.238**	1.324	1.327	1.286	1.363	1.317	**1.215**	**1.206**	1.285
		36	1.325	1.435	1.365	1.410	**1.266**	**1.252**	1.394	**1.249**	**1.282**	**1.280**	1.334
		48	1.415	**1.298**	1.550	1.429	1.442	1.449	1.531	1.600	1.431	1.440	**1.375**
	Security	6	124.9	**124.5**	125.5	**123.9**	**118.9**	**119.2**	**121.6**	125.0	**123.8**	**123.5**	**122.7**
		8	124.9	**123.0**	**123.3**	125.6	**123.2**	**123.5**	**124.5**	**123.3**	**123.3**	**124.2**	**124.8**
		10	126.5	127.1	**125.6**	**124.8**	129.0	**124.7**	127.1	**125.5**	**123.6**	**124.8**	127.3
		12	125.1	**123.4**	126.5	125.9	126.0	125.5	127.1	126.5	**124.8**	127.7	125.6
	Social Good	6	0.804	**0.782**	0.808	**0.800**	**0.796**	0.860	**0.774**	0.847	**0.800**	0.821	0.807
		8	0.912	**0.886**	**0.880**	**0.872**	**0.897**	**0.899**	0.918	**0.899**	**0.899**	**0.902**	**0.858**
		10	0.954	**0.950**	0.970	0.976	0.970	**0.948**	0.958	0.971	0.964	**0.933**	0.958
		12	0.993	1.007	**0.939**	**0.963**	1.007	**0.980**	**0.991**	**0.927**	0.998	**0.984**	1.007
	Traffic	6	0.232	0.244	0.260	0.253	0.275	0.297	**0.205**	0.246	**0.224**	**0.216**	0.258
		8	0.240	0.261	0.249	0.279	0.245	0.270	0.241	0.249	0.265	0.258	0.270
		10	0.265	**0.257**	**0.239**	**0.233**	**0.223**	0.312	**0.223**	**0.225**	**0.241**	0.276	**0.246**
		12	0.260	**0.252**	**0.247**	**0.244**	0.262	0.292	**0.237**	**0.257**	**0.232**	**0.242**	**0.240**

Table 79: Multimodal fusion strategies with **Transformer** (+ **Doc2Vec**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Transformer	Agriculture	6	0.138	0.160	**0.138**	**0.095**	**0.097**	0.143	0.285	**0.126**	0.162	0.151	0.143
		8	0.155	0.223	0.179	0.218	**0.152**	0.281	0.446	0.183	0.201	0.253	0.181
		10	0.202	0.317	0.236	**0.195**	**0.115**	**0.181**	0.677	0.245	**0.192**	**0.184**	**0.197**
		12	0.195	0.273	0.274	0.224	**0.146**	0.373	0.534	0.268	0.207	0.205	0.324
	Climate	6	1.023	**0.990**	1.023	**1.019**	**0.971**	**1.009**	1.091	1.058	1.080	1.032	1.087
		8	1.048	1.060	1.106	**1.023**	1.057	1.050	1.068	1.104	**1.040**	1.061	**1.041**
		10	1.094	**1.061**	**1.067**	1.099	1.097	**0.985**	**1.040**	**1.067**	**1.048**	1.106	**1.070**
		12	1.021	**1.007**	1.051	1.067	1.088	1.082	1.023	1.039	1.037	1.060	1.105
	Economy	6	0.252	**0.244**	**0.235**	0.415	**0.108**	0.284	0.526	**0.248**	0.447	**0.160**	0.309
		8	0.259	0.538	**0.208**	0.331	**0.062**	0.460	0.735	0.266	0.428	**0.148**	**0.244**
		10	0.288	0.711	**0.217**	**0.189**	**0.110**	**0.104**	1.452	**0.251**	**0.191**	**0.098**	**0.110**
		12	0.265	0.342	0.556	**0.186**	**0.088**	0.567	0.937	0.476	**0.052**	0.513	0.392
	Energy	12	0.085	0.132	0.102	0.143	0.117	0.109	0.124	0.095	0.101	0.098	0.106
		24	0.204	0.222	**0.200**	0.303	0.269	0.232	0.224	0.218	0.204	**0.185**	0.241
		36	0.357	0.422	0.366	**0.308**	**0.314**	**0.278**	**0.270**	**0.335**	**0.346**	**0.312**	**0.298**
		48	0.479	0.490	**0.405**	0.485	**0.399**	**0.402**	**0.422**	**0.369**	**0.435**	**0.441**	0.481
	Environment	48	0.407	0.524	0.430	0.448	0.465	0.442	0.501	0.428	0.466	0.410	0.410
		96	0.487	**0.466**	**0.454**	**0.465**	**0.423**	**0.448**	0.523	**0.470**	**0.465**	**0.433**	0.491
		192	0.445	0.528	0.452	0.519	0.460	0.468	0.651	0.463	**0.442**	0.452	**0.442**
		336	0.449	0.478	0.464	0.477	0.538	0.477	0.555	0.474	**0.408**	0.458	**0.434**
	Public Health	12	0.968	1.069	1.119	1.161	1.087	1.040	1.062	1.287	1.068	**0.961**	**0.962**
		24	1.285	1.288	**1.221**	1.352	**1.153**	1.293	1.449	**1.208**	1.322	1.296	**1.207**
		36	1.318	1.321	**1.294**	1.345	**1.282**	1.413	**1.198**	**1.265**	**1.295**	**1.288**	**1.277**
		48	1.427	1.432	**1.300**	**1.280**	**1.391**	1.432	1.521	**1.408**	**1.389**	**1.416**	1.576
	Security	6	126.6	127.3	**126.5**	**126.0**	**122.3**	**124.0**	**124.4**	**125.9**	**124.6**	128.0	**124.5**
		8	126.1	127.5	128.3	**125.9**	**123.9**	127.6	128.5	128.4	126.9	126.7	130.4
		10	129.3	**129.3**	130.7	**128.8**	**124.1**	**128.6**	129.9	131.2	130.1	129.8	130.7
		12	128.4	**126.5**	131.3	129.9	**126.7**	130.4	131.1	130.9	129.2	129.0	**118.5**
	Social Good	6	0.698	0.737	0.769	0.781	0.795	0.743	0.724	0.770	0.765	0.741	0.764
		8	0.786	**0.779**	0.856	0.855	0.843	0.813	**0.769**	0.829	0.868	0.815	0.841
		10	0.888	**0.831**	0.904	**0.855**	**0.864**	0.925	**0.853**	0.929	**0.835**	0.899	0.913
		12	0.868	0.896	0.874	**0.852**	0.894	0.914	**0.867**	0.983	0.942	**0.862**	0.940
	Traffic	6	0.161	0.162	0.163	0.167	0.173	0.171	**0.158**	0.163	0.185	**0.152**	0.166
		8	0.165	**0.164**	0.176	0.169	0.196	**0.159**	**0.160**	0.176	**0.162**	0.176	0.167
		10	0.181	**0.174**	0.192	**0.172**	0.199	0.194	**0.168**	0.192	0.190	**0.180**	0.208
		12	0.213	0.227	0.218	**0.209**	0.237	0.220	**0.209**	0.217	0.215	0.217	0.214

Table 80: Multimodal fusion strategies with **TSMixer** (+ **Doc2Vec**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
TSMixer	Agriculture	6	0.085	0.098	0.091	0.100	0.204	**0.084**	0.143	0.099	0.137	0.102	**0.077**
		8	0.124	0.157	0.158	0.311	0.205	0.300	0.167	0.171	**0.118**	0.128	0.174
		10	0.259	**0.199**	0.374	**0.245**	0.503	0.489	**0.213**	0.364	**0.224**	0.291	**0.205**
		12	0.606	0.809	**0.573**	0.616	0.907	0.644	**0.567**	**0.514**	1.412	0.685	**0.249**
	Climate	6	1.058	1.066	1.077	1.074	1.087	1.077	1.079	1.071	1.069	1.062	**1.048**
		8	1.092	**1.088**	**1.083**	**1.068**	1.102	1.095	1.100	1.104	1.095	**1.085**	1.098
		10	1.106	**1.104**	1.110	**1.091**	**1.105**	1.117	1.112	1.113	1.109	**1.098**	1.111
		12	1.104	1.114	1.117	1.110	1.118	**1.097**	**1.096**	1.115	1.130	1.113	**1.091**
	Economy	6	0.045	0.061	0.056	0.097	0.133	0.049	0.128	0.195	0.067	0.047	**0.036**
		8	0.036	0.109	0.126	0.071	0.346	0.213	0.208	0.244	0.090	0.054	0.093
		10	0.358	0.416	**0.174**	**0.239**	**0.165**	0.971	**0.203**	0.572	**0.297**	**0.223**	**0.158**
		12	0.792	**0.736**	1.217	0.876	1.525	**0.485**	**0.440**	**0.226**	1.956	0.835	**0.111**
	Energy	12	0.157	0.172	**0.150**	0.170	0.167	**0.137**	0.178	**0.127**	**0.144**	**0.143**	**0.149**
		24	0.264	0.272	0.289	0.330	0.276	0.271	0.276	**0.251**	0.276	0.304	0.278
		36	0.361	**0.360**	0.377	0.403	0.363	**0.348**	0.366	**0.338**	0.370	**0.355**	**0.333**
		48	0.454	0.456	0.474	0.465	**0.446**	**0.437**	0.459	**0.438**	0.484	0.469	0.459
	Environment	48	0.539	0.587	0.716	0.769	0.576	**0.516**	0.718	**0.521**	0.543	0.663	**0.518**
		96	0.606	0.647	0.738	1.042	0.648	0.625	0.732	**0.592**	0.664	0.637	**0.565**
		192	0.660	0.718	0.680	0.697	0.674	**0.633**	1.066	**0.592**	0.693	0.674	**0.588**
		336	0.586	0.660	0.663	0.670	**0.567**	0.595	0.892	**0.569**	0.631	0.643	**0.580**
	Public Health	12	1.074	1.116	1.208	1.222	**1.062**	1.127	1.101	1.163	1.121	1.106	**1.050**
		24	1.425	1.504	**1.389**	1.497	1.432	1.503	1.563	**1.404**	1.513	**1.395**	**1.366**
		36	1.488	**1.447**	**1.434**	**1.392**	1.493	1.536	1.509	1.523	**1.481**	**1.465**	1.565
		48	1.605	1.644	1.626	**1.602**	1.759	1.705	1.683	**1.541**	1.669	**1.575**	**1.526**
	Security	6	128.2	128.2	129.8	**127.2**	**124.9**	**125.7**	128.8	**123.1**	**124.1**	**125.9**	**127.9**
		8	127.8	**123.5**	127.8	128.6	**122.3**	**122.7**	130.2	**126.7**	**126.2**	**127.7**	**125.9**
		10	129.9	**129.7**	130.2	131.9	**123.7**	**124.6**	**124.9**	131.9	130.1	130.1	**127.9**
		12	130.2	133.3	132.1	133.5	132.2	**127.8**	**128.9**	133.7	130.5	**129.7**	**129.7**
	Social Good	6	0.744	0.748	0.782	**0.738**	0.745	**0.730**	**0.730**	0.824	**0.744**	0.772	**0.733**
		8	0.883	0.914	1.065	0.934	0.889	**0.857**	0.891	0.934	**0.817**	**0.831**	**0.823**
		10	0.890	**0.851**	0.912	**0.841**	0.897	0.932	0.893	0.900	**0.837**	0.892	**0.886**
		12	0.881	0.888	0.926	0.913	1.267	0.905	1.230	0.976	0.986	0.887	0.888
	Traffic	6	0.214	**0.201**	0.228	**0.204**	**0.206**	0.228	0.226	0.230	0.226	**0.207**	**0.187**
		8	0.212	0.220	0.223	0.213	0.226	0.222	0.235	0.275	0.276	**0.201**	**0.188**
		10	0.222	0.229	0.243	0.225	**0.222**	0.292	**0.218**	0.266	0.304	0.231	**0.207**
		12	0.289	**0.289**	0.297	0.304	0.451	**0.274**	**0.268**	0.347	0.504	**0.259**	**0.262**

Table 81: Multimodal fusion strategies with **Informer** (+ **Doc2Vec**).

TS Model	Dataset	H	Unimodal	Additive			Concat			Constrained			
				First	Middle	Last	First	Middle	Last	Orthogonal	FiLM	Gating	**CFA**
Informer	Agriculture	6	0.228	0.468	0.342	0.249	0.240	0.306	0.270	0.244	**0.212**	**0.200**	**0.218**
		8	0.307	0.398	**0.204**	**0.276**	**0.233**	**0.199**	0.390	**0.254**	**0.264**	**0.184**	**0.232**
		10	0.369	**0.267**	0.392	0.450	0.572	**0.256**	0.411	0.382	**0.363**	0.371	**0.341**
		12	0.570	0.609	0.584	0.625	**0.463**	**0.553**	**0.485**	**0.274**	**0.358**	**0.352**	**0.517**
	Climate	6	1.091	**1.045**	1.093	**1.063**	**1.029**	**1.062**	**1.068**	**1.066**	**1.051**	**1.026**	**1.016**
		8	1.127	**1.030**	**1.062**	**1.094**	**1.003**	**1.055**	**1.065**	**1.058**	**1.082**	**1.041**	**1.032**
		10	1.052	1.061	**1.050**	1.084	**0.883**	1.076	1.068	1.076	1.058	1.083	1.091
		12	1.058	1.084	1.071	1.074	**0.907**	**1.024**	1.069	1.065	1.064	1.069	1.103
	Economy	6	0.552	0.667	0.726	**0.404**	**0.543**	0.603	0.943	**0.192**	**0.510**	**0.526**	**0.381**
		8	0.704	0.852	**0.700**	0.904	**0.271**	0.812	**0.450**	**0.618**	**0.464**	**0.387**	0.720
		10	0.864	**0.741**	**0.662**	**0.727**	1.073	0.928	**0.813**	**0.757**	0.940	**0.597**	**0.276**
		12	1.015	**0.894**	**0.254**	1.273	**0.515**	1.101	**0.767**	**0.979**	1.081	**1.011**	1.057
	Energy	12	0.190	**0.177**	0.208	0.216	0.214	**0.183**	**0.174**	0.203	0.225	0.200	0.205
		24	0.276	0.297	0.408	0.294	**0.263**	0.359	**0.255**	0.341	0.323	0.374	0.286
		36	0.371	0.401	0.452	0.374	**0.364**	0.418	0.381	0.431	**0.320**	0.411	0.481
		48	0.490	**0.480**	0.510	0.520	**0.481**	0.508	0.516	**0.483**	**0.457**	**0.463**	0.501
	Environment	48	0.412	0.593	0.424	0.509	0.502	0.436	0.506	0.455	0.459	0.474	0.449
		96	0.411	0.501	0.505	0.527	0.478	0.456	0.527	0.429	0.461	0.455	0.441
		192	0.445	0.458	0.482	0.588	0.576	0.480	0.486	0.468	0.460	0.452	0.448
		336	0.436	0.512	0.478	0.489	0.500	0.455	0.548	0.493	0.458	0.452	0.461
	Public Health	12	1.061	1.124	1.109	1.116	1.103	**0.994**	**1.004**	1.097	1.105	1.125	1.091
		24	1.293	1.334	1.409	1.338	1.359	1.416	1.348	1.405	**1.288**	1.326	**1.287**
		36	1.436	**1.416**	**1.415**	1.534	**1.228**	**1.403**	1.548	1.461	1.443	1.451	1.509
		48	1.556	1.657	1.634	1.671	**1.332**	1.669	1.574	1.665	1.772	1.618	1.646
	Security	6	124.2	127.0	126.6	128.0	125.7	128.0	124.4	128.6	127.1	127.8	127.2
		8	122.3	127.7	128.0	129.0	128.8	128.4	127.3	130.1	126.7	127.5	128.8
		10	129.5	130.2	**125.6**	**127.0**	131.3	**129.2**	**128.8**	**129.4**	**129.0**	**128.4**	129.9
		12	130.8	131.3	130.9	**129.5**	**127.4**	**126.5**	**130.4**	131.1	**127.3**	132.3	**129.9**
	Social Good	6	0.725	0.754	0.790	0.727	0.752	0.757	0.766	**0.711**	0.747	0.770	0.756
		8	0.801	**0.769**	**0.788**	0.801	0.809	**0.800**	0.808	0.824	0.803	0.834	0.816
		10	0.849	**0.838**	**0.801**	0.855	**0.783**	0.861	**0.798**	0.850	**0.837**	0.884	0.898
		12	0.911	**0.862**	0.940	**0.860**	**0.902**	**0.870**	**0.870**	0.931	**0.884**	**0.883**	**0.885**
	Traffic	6	0.180	**0.178**	0.192	**0.148**	**0.157**	**0.154**	**0.159**	**0.164**	**0.177**	**0.155**	**0.156**
		8	0.174	**0.169**	**0.167**	0.185	**0.158**	**0.170**	**0.168**	0.193	0.177	**0.163**	0.182
		10	0.208	**0.181**	**0.165**	**0.193**	**0.200**	**0.177**	**0.178**	**0.187**	**0.177**	**0.173**	**0.193**
		12	0.213	0.221	0.227	**0.210**	**0.206**	**0.212**	**0.211**	0.220	0.215	0.221	0.229