A EXTRA NOTE

A portion of the source code and data is available at anonymous repository `https://anonymous.4open.science/r/MEHGT-LKG-D17C`.

B ADDITIONAL DATA DEFINITION

As shown in Table 1, this table summarizes all node and edge types used in our graph construction, along with their names, semantic meanings, and feature descriptions. The node types include key stocks, financial entities, stock exchanges, and margin-related actors, while the edge types capture diverse relationships such as price correlation, capital flow, and financial events. The associated features are derived from both structured financial indicators and semantic embeddings generated by pretrained language models, incorporating information like time series, net cash flows, and event triples.

Nodes & Edges	Names	Notation	Descriptions and Features	Feature Notation
Node types	Key Stocks	V_t^{KS}	**Desc.:** leading companies in the subfields of green computing and new energy industries **Feat.:** time series matrix of OHLCV within an w-days window	X_{vt}^{KS}
	Other Entities	V_t^{OE}	**Desc.:** other financial entities in the FinKG **Feat.:** global semantic meaning of the input generated by FinBERT	X_{vt}^{OE}
	HKEX	V_t^{HK}	**Desc.:** Hong Kong Stock Exchange **Feat.:** time series of status of SH/SZ-HK Stock Connect within an w-days window	X_{vt}^{HK}
	Margin Financing	V_t^{F}	**Desc.:** Margin Financing **Feat.:** one-hot encoding	X_{vt}^{F}
	Securities Lending	V_t^{L}	**Desc.:** Securities Lending **Feat.:** one-hot encoding	X_{vt}^{L}
Edge types	Key Stocks—correlation—Key Stocks (undirected)	E_t^{Corr}	**Desc.:** correlation of prices among Key Stocks. **Feat.:** time series of Spearman correlation coefficients within an w-days window.	X_{et}^{Corr}
	HKEX—Invest—Stocks (directed)	V_t^{HK}	**Desc.:** Hong Kong Stock Exchange **Feat.:** Northbound capital (funds flowing via SH/SZ-HK Stock Connect)	X_{et}^{HI}
	Margin Financing—go long—Stocks (directed)	E_t^{Long}	**Desc.:** net inflows from margin financing **Feat.:** time series of net margin financing cash flows within an w-days window.	X_{et}^{Long}
	Securities Lending—go short—Stocks (directed)	E_t^{Short}	**Desc.:** net short-selling of securities **Feat.:** time series of daly securities sold short within an w-days window	X_{et}^{Short}
	Key Stocks—relationship/action—Other Entities (directed)	E_t^{SRE}	**Desc.:** triples from FEKG **Feat.:** global semantic meaning of the input generated by FinBERT	X_{et}^{SRE}
	Other Entities—relationship/action—Key Stocks (directed)	E_t^{ERS}	**Desc.:** triples from FEKG **Feat.:** global semantic meaning of the input generated by FinBERT	X_{et}^{ERS}
	Key Stocks—relationship/action—Key Stocks Key Stocks—short event (directed)	E_t^{KS}	**Desc.:** tuples from FEKG (triples and event pairs) **Feat.:** global semantic meaning of the input generated by FinBERT	x_{et}^{KS}
	Other Entities—relationship/actiont—Other Entities Other Entities—short event (directed)	E_t^{OE}	**Desc.:** tuples from FEKG (triples and event pairs) **Feat.:** global semantic meaning of the input generated by FinBERT	x_{et}^{OE}

Table 1: Data definition of multimodal heterogeneous graphs.

C IMPLEMENT DETAILS

All experiments were conducted on Linux (CentOS) operating systems with Python 3.11. The FinEX model was trained on NVIDIA A100 GPUs, while the MEHGT model and baselines were trained using NVIDIA RTX 4090 GPUs. Graph neural network components were implemented with the PyTorch Geometric (PyG) library. The environment included sufficient system memory to support large-scale training of heterogeneous and multimodal architectures.

D Supplementary Experiment

D.1 Main Comparison Results on other datasets

The performance comparison between our model and the baselines on other datasets is summarized below. The conclusions drawn from these results are consistent with those presented in the main text. The details are shown in Table 2.

Methods	Sugon (603019)						BYD (002594)					
	ACC	MCC	Precision	Recall	F1	AUC	ACC	MCC	Precision	Recall	F1	AUC
Time-series models												
Informer	0.5714	0.1791	0.6667	0.3291	0.4407	0.5750	0.6623	0.3079	**0.6000**	0.6000	0.6000	0.6088
TCN	0.5649	0.1659	0.6579	0.3165	0.4274	0.5445	0.5584	0.1545	0.4839	0.6923	0.5696	0.5167
CNN-LSTM	0.5779	0.1883	0.6667	0.3544	0.4628	0.5789	0.6234	0.2498	0.5455	0.6462	0.5915	0.5749
Graph-based models												
GAT	0.6169	0.2559	0.5862	0.8608	0.6974	0.6116	0.6429	0.3098	0.5581	0.7385	0.6358	0.6659
HGT	0.6234	0.2540	0.6615	0.5443	0.5972	0.6571	0.6558	0.3176	0.5769	0.6923	0.6294	0.6352
MAC	0.6234	0.2601	**0.6780**	0.5063	0.5797	0.6322	0.6364	0.2348	0.5918	0.4462	0.5088	0.6408
MDGNN	0.6169	0.2324	0.6190	0.6582	0.6380	0.5970	0.6104	0.3268	0.5225	**0.8923**	0.6591	0.6193
MEHGT-LKG (ours)	**0.6429**	**0.3162**	0.6034	**0.8861**	**0.7179**	**0.6693**	**0.6688**	**0.3483**	0.5875	0.7231	**0.6483**	**0.6746**
	Kunlun Tech (300418)						LONGi (601012)					
Time-series models												
Informer	0.6104	0.2102	0.5672	0.5507	0.5588	0.5719	0.6688	0.2292	0.5385	0.3889	0.4516	0.6128
TCN	0.5909	0.1640	**0.6875**	0.1594	0.2588	0.4223	0.6429	0.1535	0.4857	0.3148	0.3820	0.5828
CNN-LSTM	0.6104	0.2005	0.5818	0.4638	0.5161	0.5782	0.4156	0.1629	0.3732	**0.9815**	0.5408	0.4723
Graph-based models												
GAT	0.6104	0.2628	0.5455	0.7826	0.6429	**0.6477**	0.5714	0.2548	0.4400	0.8148	0.5714	0.5517
HGT	0.6494	0.2848	0.6230	0.5507	0.5846	0.6462	0.5649	0.2802	0.4393	0.8704	0.5839	0.6289
MAC	0.6169	0.2311	0.5676	0.6087	0.5874	0.5877	0.6234	0.2387	0.4722	0.6296	0.5397	0.6343
MDGNN	**0.6623**	**0.3264**	0.6104	0.6812	**0.6438**	0.6368	0.6883	0.3042	**0.5600**	0.5185	0.5385	0.6298
MEHGT-LKG (ours)	0.6234	0.2604	0.5647	0.6957	0.6234	0.6302	**0.6883**	**0.3275**	0.5517	0.5926	**0.5714**	**0.7135**
	Jingjia Micro (300474)						Tongwei (600438)					
Time-series models												
Informer	0.6039	0.2187	0.5714	0.7027	0.6303	0.5889	0.6234	0.1943	0.5400	0.4355	0.4821	0.5852
TCN	0.5260	0.1842	0.5034	**0.9865**	**0.6667**	0.5446	0.5519	0.2249	0.4690	0.8548	0.6057	0.5521
CNN-LSTM	0.6234	0.2456	0.6081	0.6081	0.6081	0.5703	0.5260	0.2140	0.4553	0.9032	**0.6054**	0.5603
Graph-based models												
GAT	0.6234	0.2465	0.6053	0.6216	0.6133	0.6392	0.6039	0.2171	0.5063	0.6452	0.5674	0.6048
HGT	0.6234	0.2551	0.5909	0.7027	0.6420	0.6033	0.6234	0.2255	0.5303	0.5645	0.5469	0.5640
MAC	0.6234	0.2491	0.6600	0.4459	0.5323	0.5867	0.5390	0.2137	0.4615	**0.8710**	0.6034	0.5903
MDGNN	0.6299	0.2716	0.5934	0.7297	0.6545	0.5912	**0.6429**	0.2269	**0.5814**	0.4032	0.4762	0.5403
MEHGT-LKG (ours)	**0.6623**	**0.3226**	**0.6618**	0.6018	0.6338	**0.6459**	**0.6429**	**0.2518**	0.5593	0.5323	0.5455	**0.6197**

Table 2: Prediction performance of different methods across other stock datasets

D.2 Additional Results of Market Trading Simulation

The return curves on additional datasets are shown in the figure below. The analysis based on these curves leads to conclusions consistent with those in the main text. The details are shown in Figure 1 and Table 3

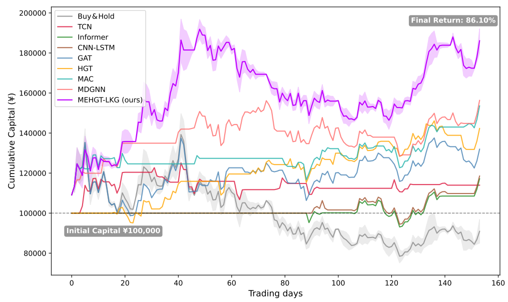
D.3 Additional Results of Ablation Study

Here, we additionally report the return performance of the ablation experiments. The details are shown in Figure 2.

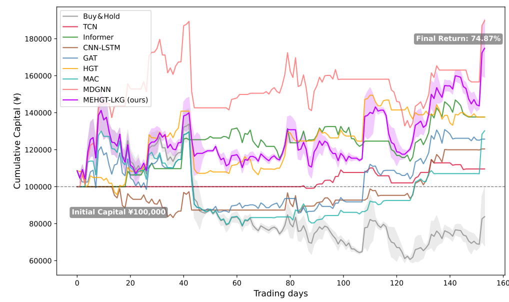
D.4 Spearman Analysis

A Spearman correlation heatmap is constructed based on the closing prices of selected key stocks, as illustrated in Figure. 3. The intensity of the color reflects the strength of the correlation: stronger positive correlations are depicted in red, whereas stronger negative correlations are shown in blue.

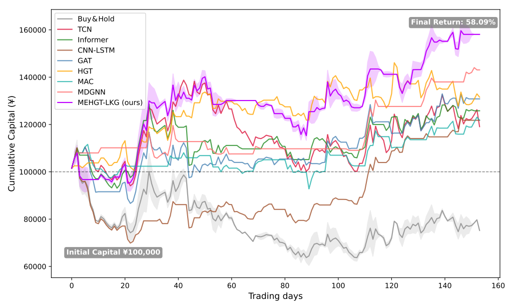
The graph shows that within sectors such as artificial intelligence and new energy, stocks often exhibit strong internal correlations. For example, the Spearman coefficient between Kunlun Tech



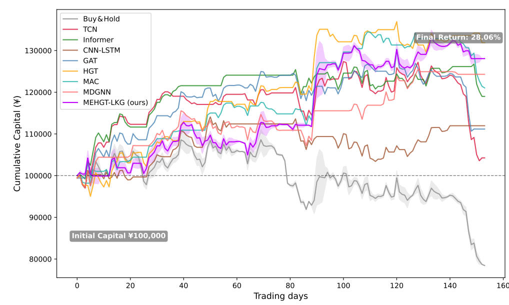
(a) Sugon (601019)



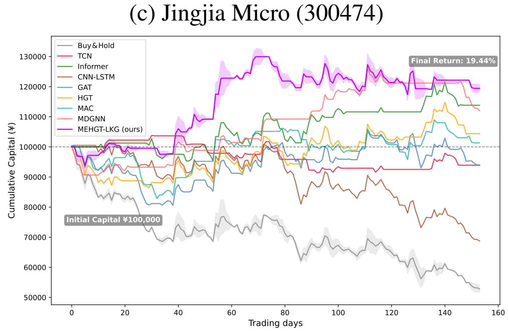
(b) Kunlun Tech (300418)



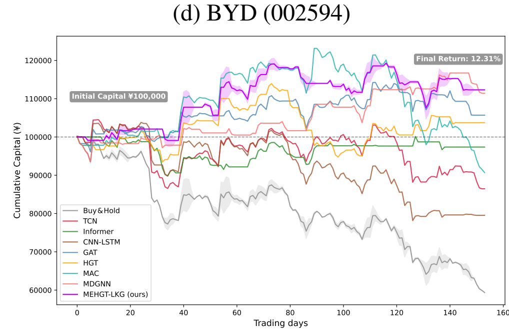
(c) Jingjia Micro (300474)



(d) BYD (002594)

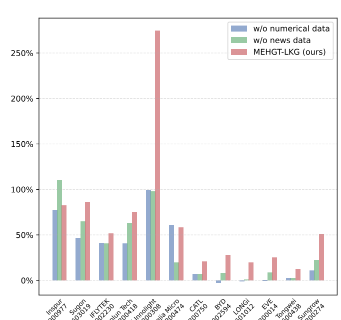


(e) LONGi (601012)

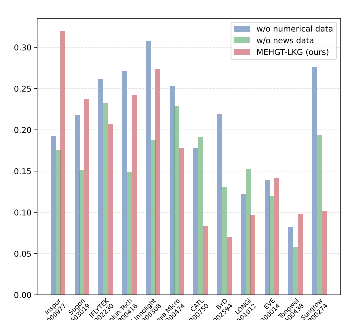


(f) Tongwei (600438)

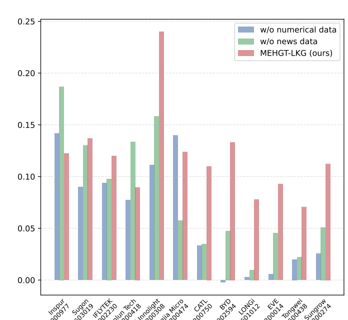
Figure 1: Simulated trading performance of all models during backtesting.



(a) CRR



(b) MDD



(c) Sharp

Figure 2: Profitability performance of ablation analysis across all stock datasets.

and Zhongji Innolight is 0.89, and between CATL and EVE is 0.87. These high values indicate shared industry factors or capital flows, leading to synchronized price movements. In contrast, cross-sector pairs, especially between AI and new energy, tend to show negative correlations. For

Stocks I	Methods	Profitability performance			Stocks II	Methods	Profitability performance		
		CRR	MDD	Sharpe			CRR	MDD	Sharp
Inspur 000977	Informer	39.1375	0.2496	1.4859	CATL 300750	Informer	-0.3439	0.1881	0.1048
	TCN	21.2760	0.2696	0.7683		TCN	-46.1522	0.5023	-1.3684
	CNN-LSTM	28.0206	0.2079	1.2795		CNN-LSTM	-50.3170	0.5062	-1.5319
	GAT	48.7005	0.2623	1.2811		GAT	3.2661	0.1636	0.3350
	HGT	46.0885	0.2546	1.4366		HGT	15.5525	0.1136	1.1398
	MAC	28.2165	0.2973	1.0461		MAC	-4.4937	0.1630	-0.3461
	MDGNN	58.2471	0.1530	2.0843		MDGNN	20.0766	0.0945	1.4430
	MEHGT-LKG (ours)	104.5015	0.1989	2.4844		MEHGT-LKG (ours)	20.8393	0.0838	1.7462
Sugon 603019	Informer	17.1574	0.1254	1.3779	BYD 002594	Informer	18.9981	0.0612	1.8414
	TCN	13.9591	0.1467	0.8461		TCN	4.2585	0.1868	0.4635
	CNN-LSTM	18.5299	0.1254	1.4795		CNN-LSTM	11.9645	0.0937	1.2065
	GAT	31.9407	0.2702	0.8620		GAT	11.1698	0.1508	0.9874
	HGT	42.3104	0.0978	2.0081		HGT	31.8891	0.0532	2.4177
	MAC	53.5646	0.1014	2.0462		MAC	21.0417	0.0996	1.8541
	MDGNN	56.3198	0.1776	1.8907		MDGNN	11.5724	0.0820	0.8191
	MEHGT-LKG (ours)	86.1013	0.2372	2.1732		MEHGT-LKG (ours)	28.0607	0.0694	2.1129
IFLYTEK 002230	Informer	6.1512	0.3228	0.4445	LONGi 601012	Informer	2.4555	0.0894	0.3191
	TCN	1.5595	0.1628	0.2556		TCN	-6.0843	0.1195	-0.7286
	CNN-LSTM	35.9297	0.1690	1.5652		CNN-LSTM	-31.2370	0.3173	-1.6541
	GAT	14.2939	0.2822	0.6382		GAT	-6.0351	0.1935	-0.1572
	HGT	26.8404	0.2601	1.0763		HGT	4.4006	0.1391	0.3635
	MAC	12.2738	0.2326	0.6969		MAC	1.3198	0.1757	0.1905
	MDGNN	43.2621	0.1283	1.7303		MDGNN	12.0417	0.1105	0.9541
	MEHGT-LKG (ours)	74.0035	0.1742	2.4209		MEHGT-LKG (ours)	19.4352	0.0967	1.2398
Kunlun Tech 300418	Informer	37.6844	0.1421	1.5573	EVE 300014	Informer	6.0840	0.1264	0.4937
	TCN	9.5881	0.0736	1.1430		TCN	-11.1429	0.1412	-0.6905
	CNN-LSTM	20.4161	0.1673	0.9239		CNN-LSTM	-12.9285	0.1926	-0.5445
	GAT	25.7172	0.3392	0.6937		GAT	3.1514	0.1957	0.3191
	HGT	37.6609	0.2443	1.0303		HGT	7.9989	0.1375	0.7413
	MAC	30.2156	0.3931	0.9842		MAC	-20.3043	0.2921	-0.8207
	MDGNN	89.8132	0.3036	1.9303		MDGNN	3.3344	0.2460	0.3651
	MEHGT-LKG (ours)	74.8732	0.2419	1.4239		MEHGT-LKG (ours)	25.2459	0.1416	1.4747
Zhongji Innolight 300308	Informer	84.3662	0.1529	2.4685	Tongwei 600438	Informer	-2.6245	0.1024	-0.2461
	TCN	65.6934	0.3317	1.7605		TCN	-13.5322	0.1728	-0.7652
	CNN-LSTM	4.4516	0.3619	0.3921		CNN-LSTM	-20.4624	0.2470	-1.2588
	GAT	124.2828	0.3976	2.3478		GAT	5.6952	0.0766	0.5508
	HGT	168.6253	0.3139	2.3542		HGT	3.7162	0.1684	0.3969
	MAC	92.7296	0.1053	3.0320		MAC	-9.3012	0.2635	-0.5096
	MDGNN	232.7633	0.1238	4.2321		MDGNN	11.4228	0.0669	1.1255
	MEHGT-LKG (ours)	274.4909	0.2735	3.8083		MEHGT-LKG (ours)	12.3115	0.0978	1.1192
Jingjia Micro 300474	Informer	25.7934	0.2017	1.0557	Sungrow 300274	Informer	6.3613	0.2230	0.4588
	TCN	19.0871	0.2782	0.7763		TCN	12.7821	0.1289	0.5032
	CNN-LSTM	21.7649	0.3655	0.9461		CNN-LSTM	33.4434	0.1288	1.2017
	GAT	30.8164	0.2158	1.1493		GAT	42.7223	0.1440	1.6319
	HGT	31.5752	0.1256	1.2969		HGT	31.9033	0.1553	1.1684
	MAC	21.8109	0.1685	1.1811		MAC	5.2465	0.1997	0.0889
	MDGNN	40.5920	0.1640	1.6081		MDGNN	28.9026	0.1380	1.2700
	MEHGT-LKG (ours)	58.0853	0.1776	1.9637		MEHGT-LKG (ours)	51.1442	0.1016	1.7827

Table 3: Profitability performance of different methods.

instance, Kunlun Tech and Tongwei have a coefficient of –0.68, reflecting divergent trends and a clear sector rotation effect, where capital shifts between the two in a see-saw pattern.

Interestingly, Inspur shows the highest cumulative Spearman correlation within its sector, totaling 3.79. Our model correspondingly achieves the best prediction performance for Inspur, with an MCC of 0.3718. This indicates that stronger correlations enhance the value of information from other stocks. During training, the model captures intrinsic price formation patterns via message passing along the Key Stocks–correlation–Key Stocks edges, leading to the best MCC for Inspur in stock trend prediction.

D.4.1 Interpretability

To investigate how the multi-head attention mechanism allocates importance across different edge types in the heterogeneous graph, we compute the average attention weights for each edge type based on the test set. Specifically, we extract the attention coefficients from each layer of MEHGTConv, aggregate them across all heads for each edge, and then compute the average attention coefficients for each edge type over all test datasets. The final results are visualized in Figure. 4.

From the graph, the proposed model shows distinct attention distributions across edge types. The edge type Key Stocks—correlation—Key Stocks receives the highest attention (0.6716), highlighting the role of stock co-movements in message aggregation. Valuable information is effectively transmitted through these structured correlations, enhancing trend prediction. For the four edge

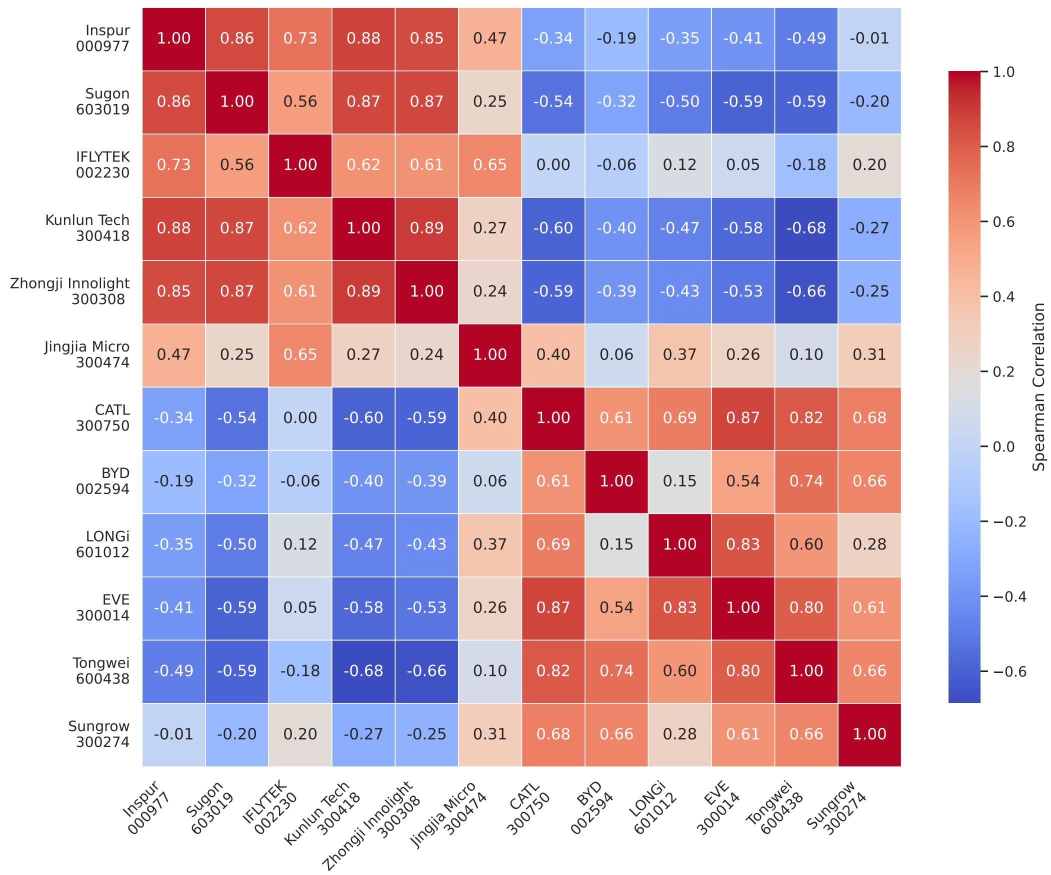


Figure 3: Spearman correlation heatmap of selected stocks.

types enriched with LLM-driven semantics, MEHGT-LKG also assigns high attention, indicating that FinEX-extracted financial events help relay relevant information to target stock nodes. These semantic edge types complement MEHGT-LKG's edge feature processing, jointly improving information aggregation and prediction accuracy.

D.5 Related Work

D.5.1 NLP-driven methods for financial modeling.

Knowledge-driven methods have been widely applied in finance, leveraging huge structured and unstructured knowledge to improve stock prediction, investment decision making, risk management, and financial analysis. Traditional knowledge-driven methods focus mainly on the extraction of features from financial texts. For example, Schumaker & Chen (2009) explored how breaking news influences stock prices, employing various textual news representation techniques. Khadjeh Nassirtoussi et al. (2015) extracted sentiment information from breaking financial news, and further utilized them to predict stock marker accurately. Nam & Seong (2019) focused on identifying events from financial texts, and proposed a novel stock prediction model. Zhou et al. (2024) explored the impact of news sources on stock prices, and further designed a deep learning prediction model based on this novel feature.

As knowledge graph technology evolves, it has become increasingly effective at systematizing both structured and unstructured knowledge, and more scholars are using knowledge graphs to solve various financial tasks. For instance, Wang et al. (2022a) constructed a knowledge graph for online lending fraud detection through address disambiguation and mining implicit relations. Cheng et al. (2022) extracted structured event triples from financial texts to build financial knowledge graphs, and

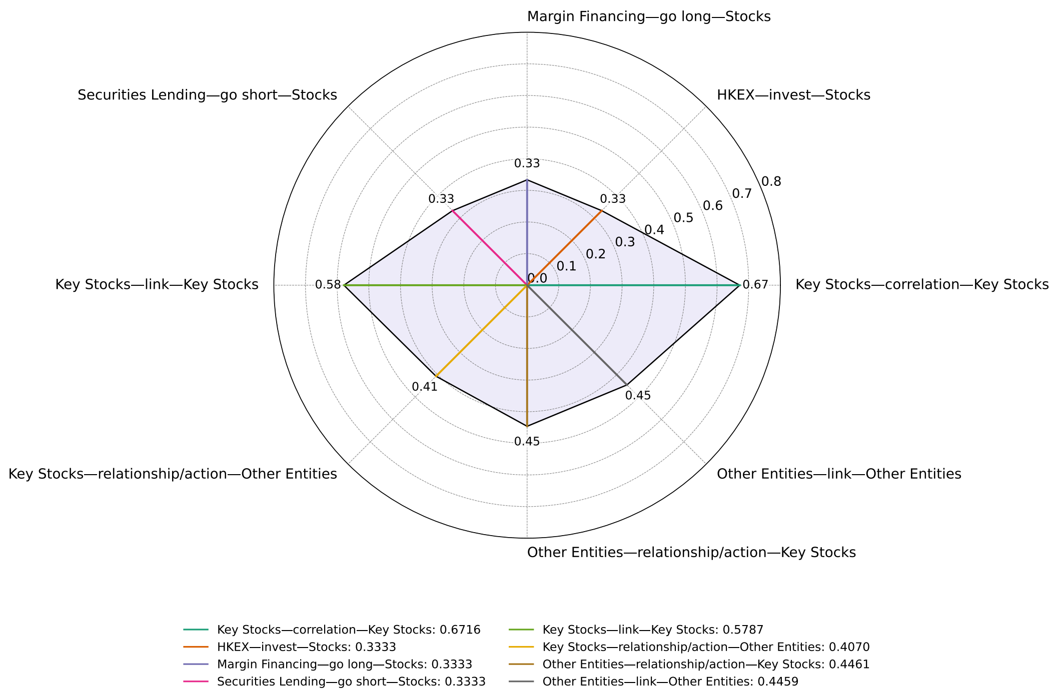


Figure 4: Average attention weights for different edge types.

proposed a multimodal GNN to forecast stock trends. Haque & Tozal (2023) introduced a knowledge graph-based method to model the relationships between medical codes, offering a graph-driven solution for fraud detection in health insurance. Wang et al. (2023) constructed a stock knowledge graph based on the fundamental information of listed companies to represent semantic and relational information among stocks, and utilized GCNs to enhance stock trend prediction performance. Song et al. (2024) formulated a knowledge graph from enterprise relational data, and proposed a multi-structure cascaded graph neural network framework (MS-CGNN) for enterprise credit risk assessment. Cai & Xie (2024) designed a two-layer knowledge graph with a semantic layer modeling financial subordination and a syntactic layer capturing articulation relations, supporting accurate and interpretable fraud detection.

Notably, in recent years, large language models (LLMs) renowned for their exceptional semantic understanding and knowledge-reasoning capabilities, have been employed in some domains for knowledge graph construction. In particular, Cheng et al. (2024) constructed a Chinese financial event knowledge graph by extracting relational triples using an LLM-based module with iterative verification, and developed a GAT-based model to improve graph completeness. Li & Sanna Passino (2024) extracted dynamic entity relations from financial texts through fine-tuning LLM, and constructed a dynamic financial knowledge graph, enabling effective predict stocks trend prediction via an attention-based GNN. Yan et al. (2025) proposed KnowNet, a system that constructs knowledge graphs by extracting entity-relation triples from LLM outputs and aligning them with validated external KGs to enhance accuracy in health information retrieval. Wang et al. (2025) introduced a novel LLM-based model to for efficient named entity recognition, enhancing knowledge graph construction across diverse domains.

In summary, knowledge-driven methods have been widely applied in financial domain and have demonstrated strong performance across various tasks. In recent years, some researchers attempted to introduce LLM into the construction of financial knowledge graphs. However, existing approaches mainly rely on prompt engineering or API-based queries, and still suffer from hallucinations, output randomness, and poor structural consistency in generating structured knowledge representations. These limitations lead to low efficiency, limited accuracy, and weak controllability in the process of knowledge graph construction. Hence, to address these issues, this study builds a high-quality, well-formatted instruction dataset based on multi-source financial texts such as news and research reports, with guidance from domain experts. A fine-tuned LLM-based module, named Event and Relationship Extraction Agent, is proposed to extract key events and corresponding structured knowledge (including triples and pairs) from long-form financial texts. This method mitigates hallucination and uncertainty during generation, significantly improving the efficiency and reliability of structured information extraction. It lays a solid foundation for high-quality financial knowledge graph construction and the subsequent modeling of knowledge-infused multimodal heterogeneous graphs.

D.5.2 STOCK PREDICTION WITH GRAPH LEARNING.

Essentially, the price volatility of stock is caused by its own market signal and the interference of related enterprises. Compared with traditional time series methods, graph learning can effectively integrate features from neighboring nodes across diverse relation types. This enriches the modeling process with structural complexity and better captures the dependencies among stocks, making it increasingly popular in stock prediction tasks. Chen et al. (2018) proposed a GCN-based stock prediction model incorporating related corporations' information, effectively capturing inter-company relations to enhance forecasting accuracy. Cheng & Li (2021). measured spillover sensitivity with respect to firm attributes and volume signals, and further designed attribute-driven graph attention network (AD-GAT) to capture dynamic influence strengths for more accurate trend forecasting. Hsu et al. (2021) explored stock and sector interactions from time series data, and subsequently proposed FinGAT to capture latent relations and improve profitable stock recommendation without predefined graphs. Chen et al. (2021) introduced a GC–CNN framework that integrates an improved GCN and a Dual-CNN structure to jointly model stock-level and market-level information, demonstrating superior performance in stock trend prediction compared to existing methods. Cheng et al. (2022) proposed MAGNN, a multi-modality graph neural network for financial time series prediction. By modeling heterogeneous sources with a two-phase attention mechanism, the model captures both intra- and inter-modality dependencies, offering interpretable and accurate forecasting results. Wang et al. (2022b) designed HATR-I, a hierarchical temporal-relational model combining dilated convolutions and dual attention over multiplex graphs to capture fine-grained stock dynamics and inter-stock relations, achieving superior performance on real-world datasets. Ma et al. (2023a) considered the dynamic nature of stock relationships and integrated motif-based similarity into graph modeling, further proposing a dynamic graph LSTM to improve trend prediction and trading profitability. To address the limitations of traditional sentiment-based methods, Ma et al. (2023b) developed a Multi-source Aggregated Classification (MAC) model, which combines numerical features, sentiment embeddings, and related stock information via GCNs, significantly improving stock price movement prediction. Zhang et al. (2025) fused sentiment, transaction, and textual data via tensor-based early fusion, and further proposed a novel dynamic attribute-driven graph attention network incorporating sentiment (AGATS), thereby enhancing stock prediction and trading performance.

Most existing methods rely on homogeneous graph learning, treating all nodes as the same type and ignoring semantic differences between entities. However, in financial markets, different types of entities (e.g., listed companies, industries, market themes, and financial events) influence stock prices in different ways. In fact, heterogeneous graph neural networks (HGNNs), owing to their capacity to model multiple types of nodes and relations, have been widely applied in various domains such as medical diagnosis and intelligent transportation. Hence, an increasing number of studies have introduced HGNNs into financial scenarios to explicitly capture the complex structural relationships among diverse types of entities and edges. This approach enables a more comprehensive representation of complex interactions among financial entities, improving the modeling and prediction of market behavior. For example, Tan et al. (2022) transformed relational market factors into heterogeneous node variables and further proposed a novel conditional heterogeneous graph neural network (FinHGNN) to predict stock price. Ma et al. (2024) fused multi-relation spillover effects and jointly modeled return and volatility, and then proposed a heterogeneous graph attention multi-task model (HGA-MT) to enhance risk-aware stock ranking for portfolio optimization. By leveraging semantic signals from earnings calls, Liu et al. (2024b) designed ECHO-GL, a novel heterogeneous graph-based model that enhances stock movement prediction with dynamic relation modeling and post earnings announcement drift processes. Liu et al. (2024a) captured cross-temporal interventions and heterogeneous stock interactions, and further proposed a dual-dynamic attention model (HD2AT) for enhancing portfolio-level financial forecasting. Qian et al. (2024) extracted multi-source stock relations and temporal dynamics, and designed the Multi-relational Dynamic Graph

Neural Network (MDGNN) to jointly model evolving inter-stock dependencies for accurate stock movement prediction.

These graph learning-based models have achieved promising results for stock prediction and investment. And, increasing studies have adopted HGNNs to model complex relationships among different types of entities in financial markets, aiming to enhance market behavior understanding and modeling. However, most existing HGNN-based methods fail to effectively process edge features such as Financial event relationships during training, leading to insufficient utilization of multi-source heterogeneous financial information. To address this limitation, we propose MEHGT model, a Multimodal Edge-enhanced Heterogeneous Graph Transformer. The proposed model embeds edge attributes directly into the computation of attention scores within the multi-head attention mechanism, allowing relation information to influence both message passing and representation learning. This further facilitates comprehensive understanding of multimodal heterogeneous graph representation and stock trend forecasting precisely.

References

Siqi Cai and Zhenping Xie. Explainable fraud detection of financial statement data driven by two-layer knowledge graph. *Expert Systems with Applications*, 246:123126, 2024.

Wei Chen, Manrui Jiang, Wei-Guo Zhang, and Zhensong Chen. A novel graph convolutional feature based convolutional neural network for stock trend prediction. *Inf. Sci.*, 556:67–94, 5 2021.

Yingmei Chen, Zhongyu Wei, and Xuanjing Huang. Incorporating corporation relationship via graph convolutional neural networks for stock price prediction. In *Proceedings of the 27th ACM international conference on information and knowledge management*, pp. 1655–1658, 2018.

Dawei Cheng, Fangzhou Yang, Sheng Xiang, and Jin Liu. Financial time series forecasting with multi-modality graph neural network. *Pattern Recognition*, 121:108218, 2022.

Haitao Cheng, Ke Wang, and Xiaoying Tan. A link prediction method for chinese financial event knowledge graph based on graph attention networks and convolutional neural networks. *Engineering Applications of Artificial Intelligence*, 138:109361, 2024.

Rui Cheng and Qing Li. Modeling the momentum spillover effect for stock prediction via attribute-driven graph attention networks. In *Proceedings of the AAAI conference on artificial intelligence*, volume 35, pp. 55–62, 2021.

Md Enamul Haque and Mehmet Engin Tozal. Identification of fraudulent healthcare claims using fuzzy bipartite knowledge graphs. *IEEE Transactions on Services Computing*, 16(6):3931–3945, 2023.

Yi-Ling Hsu, Yu-Che Tsai, and Cheng-Te Li. Fingat: Financial graph attention networks for recommending top-k k profitable stocks. *IEEE transactions on knowledge and data engineering*, 35(1): 469–481, 2021.

Arman Khadjeh Nassirtoussi, Saeed Aghabozorgi, Teh Ying Wah, and David Chek Ling Ngo. Text mining of news-headlines for forex market prediction: A multi-layer dimension reduction algorithm with semantics and sentiment. *Expert Syst. Appl.*, 42(1):306–324, 2015. ISSN 0957-4174.

Xiaohui Victor Li and Francesco Sanna Passino. Findkg: Dynamic knowledge graphs with large language models for detecting global trends in financial markets. In *Proceedings of the 5th ACM international conference on AI in finance*, pp. 573–581, 2024.

Haotian Liu, Yadong Zhou, Yuxun Zhou, and Bowen Hu. Heterogeneous dual-dynamic attention network for modeling mutual interplay of stocks. *IEEE Transactions on Artificial Intelligence*, 5 (7):3595–3606, 2024a.

Mengpu Liu, Mengying Zhu, Xiuyuan Wang, Guofang Ma, Jianwei Yin, and Xiaolin Zheng. Echo-gl: Earnings calls-driven heterogeneous graph learning for stock movement prediction. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pp. 13972–13980, 2024b.

Xiang Ma, Xuemei Li, Wenzhi Feng, Lexin Fang, and Caiming Zhang. Dynamic graph construction via motif detection for stock prediction. *Information Processing & Management*, 60(6):103480, 2023a.

Yu Ma, Rui Mao, Qika Lin, Peng Wu, and Erik Cambria. Multi-source aggregated classification for stock price movement prediction. *Information Fusion*, 91:515–528, 2023b.

Yu Ma, Rui Mao, Qika Lin, Peng Wu, and Erik Cambria. Quantitative stock portfolio optimization by multi-task learning risk and return. *Information Fusion*, 104:102165, 2024.

KiHwan Nam and NohYoon Seong. Financial news-based stock movement prediction using causality analysis of influence in the korean stock market. *Decis. Support Syst.*, 117:100–112, 2019.

Hao Qian, Hongting Zhou, Qian Zhao, Hao Chen, Hongxiang Yao, Jingwei Wang, Ziqi Liu, Fei Yu, Zhiqiang Zhang, and Jun Zhou. Mdgnn: Multi-relational dynamic graph neural network for comprehensive and dynamic stock investment prediction. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 38, pp. 14642–14650, 2024.

Robert P. Schumaker and Hsinchun Chen. A quantitative stock prediction system based on financial news. *Inf. Process. Manage.*, 45(5):571–583, 2009.

Lingyun Song, Haodong Li, Yacong Tan, Zhanhuai Li, and Xuequn Shang. Enhancing enterprise credit risk assessment with cascaded multi-level graph representation learning. *Neural Networks*, 169:475–484, 2024.

Jinghua Tan, Qing Li, Jun Wang, and Junxiao Chen. Finhgnn: A conditional heterogeneous graph learning to address relational attributes for stock predictions. *Information Sciences*, 618:317–335, 2022.

Cheng Wang, Hangyu Zhu, Ruixin Hu, Rui Li, and Changjun Jiang. Longarms: Fraud prediction in online lending services using sparse knowledge graph. *IEEE Transactions on Big Data*, 9(2): 758–772, 2022a.

Heyuan Wang, Tengjiao Wang, Shun Li, and Shijie Guan. Hatr-i: Hierarchical adaptive temporal relational interaction for stock trend prediction. *IEEE Transactions on Knowledge and Data Engineering*, 35(7):6988–7002, 2022b.

Ting Wang, Jiale Guo, Yuehui Shan, Yueyao Zhang, Bo Peng, and Zhuang Wu. A knowledge graph–gcn–community detection integrated model for large-scale stock price prediction. *Applied Soft Computing*, 145:110595, 2023.

Zhenhua Wang, Huiru Chen, Guang Xu, and Ming Ren. A novel large-language-model-driven framework for named entity recognition. *Information Processing & Management*, 62(3):104054, 2025.

Youfu Yan, Yu Hou, Yongkang Xiao, Rui Zhang, and Qianwen Wang. Knownet:guided health information seeking from llms via knowledge graph integration. *IEEE Transactions on Visualization and Computer Graphics*, 31(1):547–557, 2025. doi: 10.1109/TVCG.2024.3456364.

Qiuyue Zhang, Yunfeng Zhang, Fangxun Bao, Yang Ning, Caiming Zhang, and Peide Liu. Graph-based stock prediction with multisource information and relational data fusion. *Information Sciences*, 690:121561, 2025.

Quanshi Zhou, Lifen Jia, and Wei Chen. A deep learning-based model for stock price prediction under consideration of financial news publishers. *International Journal of General Systems*, pp. 1–41, 2024.