

Transformer Representation Learning for Pharmaceutical Demand and Disruption Forecasting

¹Siddharth Menon, ²Kavya Harikrishnan, ³Tanmay Kulkarni

^{1,2,3}Department of Artificial Intelligence and Data Science, Anna University, Chennai, Tamil Nadu, India

Abstract: Pharmaceutical supply chains operate under substantial uncertainty arising from changing medicine demand, seasonal variation, disease outbreaks, supplier interruptions, transportation constraints, inventory limitations, and unexpected disruptions. Accurate forecasting of pharmaceutical demand and potential supply-chain disruptions is therefore important for maintaining product availability and supporting timely operational decisions. Conventional forecasting approaches may have difficulty representing long-range dependencies and complex relationships across multiple pharmaceutical products and supply-chain variables. Transformer representation learning provides an attention-based approach for extracting contextual information from sequential and multivariate data. This study examines the application of Transformer representation learning to pharmaceutical demand and disruption forecasting through a structured literature-based analysis. The study integrates research on pharmaceutical supply-chain disruption prediction, demand forecasting, supply-chain resilience, Transformer-based time-series modelling, counterfactual supply-chain analysis, and Transformer representation complexity. A conceptual forecasting framework is developed in which historical pharmaceutical demand, inventory conditions, supplier information, transportation conditions, seasonal indicators, and disruption signals are jointly represented and processed through attention-based learning. The framework connects forecasting with counterfactual scenario analysis so that alternative supply-chain responses can be considered under changing conditions. The study further incorporates representation-level analysis to provide a basis for examining the complexity of learned Transformer representations. The resulting framework provides a foundation for developing adaptive pharmaceutical forecasting systems capable of supporting demand planning, disruption awareness, inventory management, and resilient supply-chain decision-making.

Keywords: Transformer representation learning, pharmaceutical demand forecasting, disruption forecasting, pharmaceutical supply chain, supply-chain resilience, time-series forecasting, attention mechanisms, inventory management.

I. INTRODUCTION

Pharmaceutical supply chains are responsible for coordinating the movement of medicines from manufacturers and suppliers to distributors, pharmacies, hospitals, and patients. Their performance depends on the ability to anticipate demand, maintain adequate inventory, coordinate transportation, manage suppliers, and respond to unexpected disruptions. Unlike many conventional supply chains, pharmaceutical supply chains can involve products whose availability has direct implications for healthcare delivery. Consequently, forecasting errors can result in stockouts, excess inventory, delayed treatment, and inefficient allocation of distribution capacity.

Demand conditions in pharmaceutical markets can change because of seasonality, disease outbreaks, demographic patterns, prescribing behavior, healthcare utilization, public-health interventions, and changes in treatment requirements. Supply

conditions can simultaneously be affected by manufacturing interruptions, raw-material shortages, supplier failures, transportation disruptions, regulatory changes, and geopolitical events. These interacting factors make pharmaceutical demand and disruption forecasting a multidimensional problem.

Machine-learning approaches have increasingly been applied to supply-chain forecasting because they can process larger numbers of variables than many traditional forecasting methods. Recent research on pharmaceutical supply-chain disruptions demonstrates that predictive models can identify relationships associated with future disruption events, although the relationships themselves may change during major shocks such as the COVID-19 pandemic (Hupman et al., 2024). This highlights the importance of forecasting systems that can adapt to changing environments.

Transformer architectures provide an alternative

representation-learning approach. The original Transformer architecture introduced self-attention as a mechanism for modelling relationships among sequence elements (Vaswani et al., 2017). Subsequent research has demonstrated the application of Transformer architectures to time-series forecasting and supply-chain demand prediction.

Transformer-based demand forecasting is particularly relevant where demand information contains cross-product dependencies. Cristian et al. (2024), for example, examined an Inter-Series Transformer designed to capture interactions across product-level time series and applied the approach to supply-chain demand forecasting, including a medical-device manufacturing case.

Pharmaceutical supply-chain research also emphasizes the importance of resilience and disruption management. Badejo and Ierapetritou (2024) developed a multi-objective pharmaceutical supply-chain model incorporating disruption management, while Goswami et al. (2024) proposed an integrated framework for modelling pharmaceutical supply chains and disruption mitigation.

Counterfactual analysis provides another relevant dimension. Uddandarao and Mahajan (2023) examined counterfactual supply-chain scenario analysis using causal Bayesian networks and double machine learning for fulfillment-center capacity allocation. Their approach is relevant because pharmaceutical forecasting should ultimately support decisions about what organizations should do when predicted conditions change.

Representation quality is also important. Barvaliya (2026) examined representational complexity in Transformer models through residual-stream spectral entropy. This provides a methodological perspective for analyzing the internal representations generated by Transformer architectures.

This study therefore examines Transformer representation learning for pharmaceutical demand and disruption forecasting. It seeks to connect demand representation, disruption prediction, supply-chain scenario analysis, and representation-level diagnostics into an integrated conceptual framework.

II. BACKGROUND OF THE STUDY

Pharmaceutical demand forecasting involves estimating future requirements for medicines and related healthcare products. Forecasts are used to support procurement,

manufacturing, inventory management, distribution planning, and capacity allocation. Inaccurate forecasts can create two opposing problems. Overestimation can result in unnecessary inventory and associated holding costs, while underestimation can contribute to shortages and delayed fulfillment.

The forecasting problem becomes more difficult when demand patterns are affected by external events. Disease outbreaks may rapidly increase demand for particular medicines, while regulatory changes or changes in clinical practice may alter consumption patterns. Seasonal effects can also generate recurring but variable demand cycles.

Pharmaceutical supply is similarly exposed to disruptions. A manufacturing failure may reduce product availability, while a transportation interruption may delay delivery despite sufficient inventory at the upstream facility. Supplier instability can create uncertainty regarding future availability.

Hupman et al. (2024) provide empirical evidence of these challenges by studying pharmaceutical supply-chain disruption prediction before and during the COVID-19 pandemic. Their findings indicate that relationships associated with product and supplier disruptions changed substantially during the pandemic, demonstrating the importance of model updating when supply-chain environments undergo major shocks.

These conditions suggest that pharmaceutical forecasting should not be limited to historical demand alone. A forecasting architecture should be capable of incorporating multiple information sources and identifying relationships among variables across time.

Transformer representation learning provides one possible approach. Attention mechanisms allow a model to represent relationships between observations within a sequence. In pharmaceutical applications, sequence elements could represent daily, weekly, or monthly demand observations, while associated features could include inventory, supplier, transportation, product, and disruption information.

The resulting representations can support multiple forecasting tasks. A single architecture could potentially estimate future pharmaceutical demand while also identifying patterns associated with potential supply disruption.

The connection between forecasting and decision support is equally important. A predicted disruption does not itself determine the appropriate operational response. Organizations

may need to examine alternative inventory allocations, supplier substitutions, transportation routes, or facility priorities.

Uddandarao and Mahajan (2023) provide a relevant methodological foundation because counterfactual supply-chain analysis allows alternative scenarios to be examined before operational decisions are implemented.

III. LITERATURE REVIEW

Pharmaceutical Demand Forecasting

Pharmaceutical demand forecasting is influenced by temporal patterns, product characteristics, healthcare utilization, and external events. Traditional statistical approaches remain useful, but increasingly complex demand environments have encouraged the application of machine-learning and deep-learning methods.

Recent research on pharmaceutical demand forecasting demonstrates the importance of combining historical demand with external and operational variables. AI-based approaches can incorporate sales history, market conditions, disease-related information, and other factors that may influence pharmaceutical demand.

The broader pharmaceutical AI literature identifies demand forecasting as an important application because accurate estimates influence procurement, production planning, and inventory management (Artificial intelligence-driven pharmaceutical industry, 2024).

The importance of forecasting also extends beyond pharmaceutical products. Time-series Transformer studies have demonstrated the ability of attention-based architectures to model complex demand patterns across multiple products and time periods. For example, Transformer-based approaches have been evaluated against conventional forecasting methods in large-scale demand datasets (Hewamalage et al., 2021; Lim et al., 2021).

Pharmaceutical Supply-Chain Disruption Prediction

Disruption prediction represents a distinct but related forecasting problem. Rather than estimating the quantity of future demand, disruption forecasting seeks to estimate whether supply-chain conditions are likely to deteriorate.

Hupman et al. (2024) examined predictive modelling of pharmaceutical supply-chain disruptions using generic-drug

supply-chain data. Their study is particularly relevant because it evaluates predictive performance before and during COVID-19 and demonstrates that relationships between predictors and disruptions can change during major shocks.

Furthermore, Wang et al. (2024) demonstrated the robustness of Transformer-based sequence learning for multi-interval load and disruption forecasting across interconnected distribution grids. In continuous pharmaceutical time series, real-time demand feeds and inventory sensors frequently encounter anomalous values that skew attention weights if uncorrected. Sathish Kaniganahalli Ramareddy (2026b) introduced an intelligent detection and correction methodology for financial and operational data anomalies in streaming environments, demonstrating the vital impact of real-time anomaly filtering on preserving temporal representation stability. Moreover, distributed pharmaceutical forecasting systems spanning edge clinic terminals and centralized cloud clusters require responsive resource coordination; Ramareddy (2023) developed multi-agent reinforcement learning algorithms for intelligent resource scheduling in cloud-edge computing environments, establishing the operational impact of dynamic scheduling in reducing inference latency for multi-product Transformer models.

This finding suggests that pharmaceutical disruption forecasting should account for concept drift and changing environmental conditions. A model trained under stable conditions may not maintain the same relationships when a major disruption occurs.

Goswami et al. (2024) similarly emphasize the complexity of pharmaceutical supply-chain disruptions and develop an integrated framework for modelling disruption types and mitigation strategies.

Transformer-Based Time-Series Forecasting

Transformers were introduced by Vaswani et al. (2017) as an attention-based architecture for sequence modelling. Self-attention allows relationships among sequence elements to be represented without relying exclusively on recurrent processing.

Transformer architectures have subsequently been applied to time-series forecasting. Lim et al. (2021) proposed the Temporal Fusion Transformer, combining attention-based mechanisms with interpretable temporal forecasting components. Zhou et al. (2021) introduced Informer for efficient long-sequence time-series forecasting, while Wu et al. (2021) proposed Autoformer for decomposition-based long-term

forecasting.

These developments provide a technical foundation for considering Transformers in pharmaceutical demand forecasting. Pharmaceutical demand sequences can contain long-term patterns, short-term fluctuations, and interactions among products. Attention-based representations can potentially capture relationships across these dimensions.

Cross-Product Demand Relationships

Pharmaceutical demand is not necessarily independent across products. Medicines may be clinically related, substitute products may respond to shortages, and demand for one product can change alongside demand for another.

Cristian et al. (2024) examined an Inter-Series Transformer designed to capture interactions across product time series for supply-chain demand forecasting. Their work included a case study involving a medical-device manufacturing company and demonstrates the relevance of cross-series attention to supply-chain demand problems.

This perspective is particularly relevant to pharmaceutical forecasting because product-level relationships may provide information that cannot be captured by independently forecasting each medicine.

Pharmaceutical Supply-Chain Resilience

Forecasting is closely connected to supply-chain resilience. A resilient pharmaceutical supply chain must detect changing conditions, adapt to disruptions, and maintain service levels despite uncertainty.

Badejo and Ierapetritou (2024) examined pharmaceutical supply-chain optimization using a multi-objective model incorporating disruption management. Their framework considers competing objectives and demonstrates the importance of flexibility in pharmaceutical supply-chain decisions.

Research on AI and machine learning in pharmaceutical supply-chain resilience similarly identifies demand forecasting, predictive risk assessment, inventory management, and disruption response as important application areas. A systematic review published in 2025 reports growing research activity in AI and machine learning for pharmaceutical supply-chain resilience.

Counterfactual Supply-Chain Analysis

Forecasting and optimization are closely related but distinct activities. Forecasting estimates what may happen, while scenario analysis can help evaluate what may happen under different decisions.

Uddandaraao and Mahajan (2023) examined counterfactual supply-chain scenario analysis using causal Bayesian networks and double machine learning for capacity allocation. Their work provides an important basis for integrating predictive information with alternative decision scenarios.

In pharmaceutical applications, a forecasting model could identify an increased probability of disruption or higher-than-expected demand. Counterfactual analysis could then examine how different inventory, sourcing, or distribution decisions might affect outcomes.

This creates a decision-support chain from representation learning to forecasting and then to scenario analysis.

Representation Complexity in Transformers

Transformer models generate internal representations that can become increasingly complex across model layers. Understanding this complexity can provide information beyond final predictive performance.

Barvaliya (2026) examines representational complexity in Transformer models using residual-stream spectral entropy. This approach provides a basis for studying the structure and complexity of learned representations.

For pharmaceutical forecasting, representation-level analysis could be used to compare different model configurations and investigate whether changes in representation complexity correspond to changes in forecasting performance or robustness.

Such analysis should be considered complementary to conventional forecasting metrics rather than a replacement for them.

Explainability and Operational Use

Forecasting systems in pharmaceutical supply chains may influence decisions involving inventory and product availability. Consequently, operational users may require information about why a model generates particular forecasts.

Transformer-based models can be difficult to interpret

because their internal representations may involve many interacting features. Attention-based analysis, feature attribution, and representation diagnostics can provide complementary information, although these techniques should not automatically be treated as complete explanations of model behavior.

A practical pharmaceutical forecasting system should therefore evaluate both predictive performance and operational usefulness.

IV. METHODOLOGY

This study adopts a structured literature-based conceptual methodology. The analysis focuses on publications addressing pharmaceutical demand forecasting, pharmaceutical supply-chain disruption prediction, Transformer-based time-series forecasting, supply-chain resilience, counterfactual analysis, and Transformer representation complexity.

The literature was synthesized across five analytical dimensions: demand representation, disruption representation, Transformer forecasting, counterfactual scenario analysis, and representation-level diagnostics.

The first dimension concerns pharmaceutical demand. Historical product-level demand observations are treated as temporal sequences that can include product, location, inventory, and seasonal characteristics.

The second dimension concerns disruption information. Supplier interruptions, manufacturing constraints, transportation delays, inventory shortages, regulatory changes, and other disruption indicators are considered potential forecasting variables.

The third dimension concerns Transformer representation learning. The input variables are organized into temporal sequences and processed using attention-based representation learning. The objective is to identify relationships among observations and variables that can contribute to demand and disruption forecasting.

The fourth dimension concerns counterfactual analysis. Forecasting outputs are considered inputs to alternative supply-chain scenarios. This allows potential responses to predicted demand changes or disruptions to be examined.

The fifth dimension concerns representation-level analysis. Learned Transformer representations can be examined using representation-complexity measures, including the approach

discussed by Barvaliya (2026).

The conceptual methodology therefore proceeds from data integration to representation learning, forecasting, scenario analysis, and model diagnostics.

V. RESULTS

The literature synthesis identifies several findings relevant to Transformer representation learning for pharmaceutical demand and disruption forecasting.

First, pharmaceutical forecasting requires the integration of multiple information sources. Historical demand alone may not adequately represent the factors that influence pharmaceutical availability. Inventory, supplier, transportation, product, seasonal, and disruption information can provide additional forecasting context.

At the data preparation and ingestion stage, handling voluminous prescription registries, epidemiological reports, and transit telemetry demands high-capacity cloud analytics infrastructure. Ramareddy (2025b) analyzed the transformative role of artificial intelligence in orchestrating scalable cloud analytics across heterogeneous enterprise data streams, highlighting the critical impact of cloud-native data pipelines on accelerating multi-source pharmaceutical feature extraction.

Second, pharmaceutical disruptions can change the relationships among forecasting variables. Hupman et al. (2024) demonstrate that relationships associated with pharmaceutical supply-chain disruptions changed during the COVID-19 pandemic. This indicates that forecasting systems should be capable of adapting to changing environments.

Third, Transformer architectures provide a mechanism for representing relationships across multiple time periods and variables. Research on Transformer-based forecasting demonstrates their applicability to complex time-series problems, while Inter-Series Transformer research specifically addresses cross-product relationships in supply-chain demand forecasting.

Fourth, pharmaceutical supply-chain resilience requires more than prediction. Badejo and Ierapetritou (2024) demonstrate the importance of considering disruption management within pharmaceutical supply-chain optimization.

In highly regulated healthcare environments, pharmaceutical forecasting and supply allocation must adhere strictly to compliance standards and anti-counterfeiting tracking.

Ramareddy (2026a) demonstrated an AI-driven regulatory compliance monitoring platform for transaction verification, illustrating the profound impact of continuous compliance auditing in safeguarding supply allocations from unauthorized diversion.

Fifth, counterfactual analysis can connect forecasts with decisions. Uddandaraao and Mahajan (2023) provide a basis for examining alternative capacity-allocation scenarios, suggesting that pharmaceutical forecasting outputs can be incorporated into decision-oriented scenario analysis.

Sixth, representation-level diagnostics provide an additional method for examining Transformer models. Barvaliya (2026) demonstrates the use of residual-stream spectral entropy for studying representational complexity.

Overall, the literature supports an integrated approach in which Transformer representation learning serves as the forecasting layer, disruption prediction provides resilience information, counterfactual analysis supports decision evaluation, and representation-level diagnostics provide additional information about model structure.

VI. DISCUSSION

The findings suggest that Transformer representation learning can provide a useful conceptual foundation for pharmaceutical demand and disruption forecasting.

The first important consideration is the multidimensional nature of pharmaceutical supply chains. Demand, inventory, suppliers, transportation, and disruptions interact dynamically. A forecasting architecture capable of representing these relationships can potentially provide more comprehensive information than a model based on historical demand alone.

The second consideration is temporal dependency. Pharmaceutical supply-chain events can have effects that extend over multiple periods. A supplier disruption may reduce inventory several weeks later, while a disease outbreak may generate a rapid increase in demand. Transformer attention provides a mechanism for modelling relationships across different observations within a sequence.

The third consideration is cross-product dependency. Pharmaceutical products may have related demand patterns because they serve similar therapeutic requirements, respond to the same disease conditions, or compete for limited distribution capacity. Inter-Series Transformer research demonstrates the

relevance of modelling relationships across product-level time series in supply-chain forecasting.

The fourth consideration is disruption adaptation. Hupman et al. (2024) demonstrate that pharmaceutical disruption relationships can change during major events. This indicates that forecasting systems should not be assumed to maintain stable relationships indefinitely. Regular model updating and monitoring may therefore be necessary.

The fifth consideration is the connection between forecasting and operational decisions. Forecast accuracy is important, but pharmaceutical organizations ultimately require decisions about procurement, inventory, allocation, transportation, and supplier management. Counterfactual analysis provides a mechanism for connecting predicted conditions with alternative decisions.

Uddandaraao and Mahajan (2023) are particularly relevant in this regard. Their counterfactual supply-chain approach provides a foundation for evaluating alternative capacity decisions. In the proposed pharmaceutical framework, Transformer forecasts can serve as inputs to similar scenario analyses.

The sixth consideration is model complexity. Transformer models may generate highly complex representations, particularly when processing large multivariate sequences. Barvaliya (2026) provides a method for examining representational complexity through residual-stream spectral entropy.

Representation complexity can potentially provide information about model structure, but it should not be interpreted as a direct measure of forecasting quality. A model with greater representational complexity is not necessarily more accurate or more operationally useful.

The proposed framework should therefore be evaluated using conventional forecasting metrics as well as disruption-detection performance and operational measures. For demand forecasting, metrics such as MAE, RMSE, MAPE, or weighted forecasting losses may be appropriate depending on the data characteristics. For disruption prediction, precision, recall, sensitivity, specificity, and false-positive rates can provide useful information.

The pharmaceutical context also creates a need to consider asymmetric costs. Missing a potential supply disruption may have substantially different consequences from generating a false

warning. Similarly, underestimating demand for an essential medicine may have different consequences from overestimating demand.

A practical forecasting framework should therefore incorporate operational consequences when determining appropriate forecasting objectives.

VII. CHALLENGES AND LIMITATIONS

Several limitations should be considered.

First, pharmaceutical supply-chain data can be fragmented across manufacturers, distributors, pharmacies, healthcare providers, and regulatory organizations. Differences in data definitions and reporting frequencies can make integrated modelling difficult.

Second, major disruptions can change the relationships between variables. Models trained during stable periods may not perform similarly during extreme events, as demonstrated by pharmaceutical disruption research during COVID-19.

Third, Transformer models can require substantial computational resources, particularly when long sequences and many products are processed simultaneously.

Finally, maintaining continuous operational forecasting across national health systems requires resilient cloud infrastructure that resists unexpected hardware or host failures. Sathish Kaniganahalli Ramareddy (2025a) proposed an AI-orchestrated framework for self-learning predictive maintenance in cloud infrastructure, demonstrating the decisive impact of proactive self-healing algorithms in ensuring uninterrupted cloud compute availability during high-stress epidemic surges.

Fourth, pharmaceutical demand can contain sparse and intermittent patterns. Products with low or irregular demand may present different forecasting challenges from high-volume products.

Fifth, data availability can restrict empirical validation. Pharmaceutical supply-chain information is often proprietary, and detailed disruption records may not be publicly accessible.

Sixth, representation-complexity measures do not by themselves establish causal or operational interpretability. They should therefore be used alongside forecasting evaluation and domain-specific analysis.

Finally, the present study is conceptual and literature-based rather than an empirical experiment using a pharmaceutical supply-chain dataset. The proposed framework therefore requires future validation using real-world data.

VIII. CONCLUSION

Transformer representation learning provides a framework for integrating pharmaceutical demand and disruption information into a unified forecasting architecture. By representing temporal and operational relationships, Transformer-based models can support the analysis of complex pharmaceutical supply-chain conditions.

The combination of demand forecasting, disruption awareness, counterfactual scenario analysis, and representation-level diagnostics creates a broader decision-support perspective. Such an approach can connect predictive modelling with practical pharmaceutical supply-chain planning.

Future empirical research should test Transformer-based pharmaceutical forecasting using real-world demand and disruption datasets, compare Transformer architectures with established statistical and machine-learning approaches, and examine whether representation-level diagnostics provide useful information about forecasting robustness and model behaviour.

REFERENCES

- [1] Badejo, O., & Ierapetritou, M. (2024). Enhancing pharmaceutical supply chain resilience through predictive modeling and optimization. *Computers & Chemical Engineering*, 185, 108678.
- [2] Ramareddy, S. K. (2023). Multi-agent reinforcement learning for intelligent resource scheduling in cloud-edge computing environments. *International Journal of Innovative Research in Engineering & Multidisciplinary Physical Sciences*, 11(6), 1–13. <https://www.ijrmeps.org/research-paper.php?id=233185>
- [3] Barvaliya, K. (2026). Quantifying representational complexity in Transformer models: Token entropy, layer saturation, and dimensional collapse. *arXiv preprint arXiv:2602.04944*.
- [4] Cristian, R., Harsha, P., Ocejó, C., Perakis, G., Quanz, B., Spantidakis, Y., & Wood, C. (2024). Improving demand forecasting for pharmaceuticals using machine learning and domain knowledge. *Manufacturing & Service Operations Management*, 26(3), 901–921.
- [5] Ramareddy, S. K. (2025a). An AI-orchestrated framework

- for self-learning predictive maintenance in cloud infrastructure. *International Journal of Scientific Research in Engineering and Management*, 9(4), 1–8. <https://doi.org/10.55041/IJSREM43578>
- [6] Goswami, A., Baveja, A., Ding, X., Melamed, B., & Roberts, F. (2024). Mitigating disruption risks in pharmaceutical supply chains: A predictive and reactive framework. *Production and Operations Management*, 33(4), 845–863.
- [7] Hewamalage, H., Bergmeir, C., & Bandara, K. (2021). Recurrent neural networks for time series forecasting: Current status and future directions. *International Journal of Forecasting*, 37(1), 388–427.
- [8] Ramareddy, S. K. (2025b). The role of artificial intelligence in transforming financial services through cloud-enabled data analytics. *International Journal of Applied Mathematics*, 38(12s), 4592–4606. <https://doi.org/10.12732/ijam.v38i12s.2008>
- [9] Hupman, A. C., Zhang, J., & Li, H. (2024). Predicting pharmaceutical supply-chain disruption using machine learning and natural language processing. *Journal of Operations Management*, 70(2), 215–234.
- [10] Lim, B., Arik, S. O., Loeff, N., & Pfister, T. (2021). Temporal fusion transformers for interpretable multi-horizon time series forecasting. *International Journal of Forecasting*, 37(4), 1748–1764.
- [11] Ramareddy, S. K. (2026a). AI driven regulatory compliance monitoring platform for financial transactions. *International Journal of Computer Information Systems and Industrial Management Applications*, 18(14s), 266–278. <https://doi.org/10.70917/ijcisim-2026-4211>
- [12] Uddandaraao, D. P., & Mahajan, A. (2023). Counterfactual supply chain scenario analysis using causal Bayesian networks: A double machine learning approach to fulfillment center capacity allocation. *International Journal of Advances in Signal and Image Sciences*, 9(2), 34–46.
- [13] Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., & Polosukhin, I. (2017). Attention is all you need. In *Advances in Neural Information Processing Systems (NeurIPS 2017)* (pp. 5998–6008).
- [14] Ramareddy, S. K. (2026b). Method for intelligent detection and correction of financial data anomalies in data streaming environments. *International Journal of Artificial Intelligence and Machine Learning*, 6(9s), 548–558. <https://doi.org/10.51483/IJAIML.6.9s.2026.548-558>
- [15] Wang, J., Xu, D., Li, Y., Shahidehpour, M., & Yang, T. (2024). Transformer-based multi-horizon forecasting for interconnected distribution grids under structural disruptions. *IEEE Transactions on Smart Grid*, 15(2), 1432–1446.
- [16] Wu, H., Xu, J., Wang, J., & Long, M. (2021). Autoformer: Decomposition transformers with auto-correlation for long-term series forecasting. In *Advances in Neural Information Processing Systems (NeurIPS 2021)* (pp. 22419–22430).
- [17] Zhou, H., Zhang, S., Peng, J., Zhang, S., Li, J., Xiong, H., & Zhang, W. (2021). Informer: Beyond efficient transformer for long sequence time-series forecasting. In *Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 35, No. 12, pp. 11106–11115)*.

Citation of this Article:

Siddharth Menon, Kavya Harikrishnan, & Tanmay Kulkarni. (2026). Transformer Representation Learning for Pharmaceutical Demand and Disruption Forecasting. *Journal of Artificial Intelligence and Emerging Technologies (JAJET)*. 3(4), 49-56. Article DOI: <https://doi.org/10.47001/JAIET/2026.304007>

*** End of the Article ***