

Application of Transformer Models for Demand Forecasting in FMCG Industry

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Abstract— Advanced demand forecasting techniques that adjust to changing market conditions are essential in the fast-moving consumer goods industry. This paper presents a novel method that combines demand-sensing approaches with iTransformer models, which are known for their effectiveness in processing multivariate time series data. This methodology goes beyond typical forecasting models by combining sentiment analysis from Google Trends, Amazon reviews, and competitors' analysis. The result is a comprehensive understanding of market behaviors and trends. The model is further improved with the incorporation of DistilBERT for sentiment analysis, which provides rich insights into customer sentiment. The results show that this model performs significantly better in terms of reliability and precision than traditional forecasting techniques, which is a considerable advancement. Using these technologies, FMCG companies can manage demand forecasts with higher precision.

Keywords—PyTorch, iTransformer, TimesNet, Demand Forecasting, Time-Series Forecasting

I. INTRODUCTION

Accurately predicting demand for fast-moving consumer goods (FMCG) gives businesses a particular advantage in today's fiercely competitive industry. The broad range of products offered, rapid turnover rates, and shifting consumer preferences define FMCG marketplaces. Because this industry is dynamic, traditional forecasting techniques like linear regression are static and find it difficult to adjust. As a result, companies struggle with incorrect inventory levels and decreased profitability.

More people are realizing how important it is to enhance demand forecasting in the FMCG sector. The complexity of supply chain planning is covered in an essay published in 2022 on Wolters Kluwer with the title "Supply Chain Uncertainty: A Fundamental Challenge for Supply Chain Planners". It highlights the erratic and unpredictable nature

of customer demand, which is made worse by things like marketing campaigns [1][2]. The COVID-19 aftermath and demand unpredictability have demonstrated the inadequacy of typical forecasting techniques.

Our study is aimed at addressing these difficulties. We ask two essential questions. How can improved transformer models used to analyze time series data improve the accuracy of long-term demand forecasts? Furthermore, how do external influences such as social media trends, promotional events, rival activity, and complementary product dynamics affect demand patterns?

To address these problems, we used a two-tiered strategy that combined transformer models and demand-sensing methodologies. Our research goes beyond typical data points, examining external elements like social media sentiment and promotional efforts. This holistic approach recognizes the various influences on consumer demand, resulting in a more realistic and comprehensive forecasting model.

This paper is structured to demonstrate our process and insights, and to bring a new perspective to demand forecasting. The following section offers an extensive review of existing literature on the application of transformers and demand-sensing. This sets the stage for our proposed methodology where we discuss the formulation of criteria that enabled our analysis. The parts that follow explain how we created and evaluated various models, followed by an evaluation of their performance against established forecasting methodologies. Finally, we conclude the paper with a detailed discussion of the study's ramifications and future research objectives.

With this systematic approach, we want to deliver real solutions to a sector grappling with the complexities of modern demand forecasting. Our study seeks to bridge the gap between theoretical models and real-world implementations, offering a distinct perspective on the deployment of advanced analytics in the FMCG business.

II. LITERATURE REVIEW

Accurate demand forecasting is crucial in the fast-moving consumer goods (FMCG) business, requiring creative methodologies. Advanced analytical models, such as transformers, show promise for tackling this difficulty. Transformers, which were originally created for natural language processing, excel at capturing temporal dependencies in time series data, as emphasized by Kambale et al. (2023) and further investigated by Rao et al. (2023) when dealing with multivariate scenarios. Their findings highlight transformers' ability to capture complex interactions between variables, which is critical in the dynamic FMCG industry [3][4]. Building on this, Vallés-Pérez et al. (2022) demonstrate the efficacy of deep learning approaches, namely transformer models, in sales forecasting [5].

To summarize some of the literature cited in Appendix A, the iTransformer model, described in "Transformer: Inverted Transformers are Effective for Time Series Forecasting," transforms time series analysis by prioritizing variate tokens over temporal tokens, significantly improving its ability to handle multivariate data [6]. In contrast, the Temporal Fusion Transformers (TFT) paradigm, as outlined in "Temporal Fusion Transformers for Interpretable Multi-horizon Time Series Forecasting," emphasizes interpretability and heterogeneous data integration [7]. While TFT provides detailed insights, the iTransformer's streamlined approach and computational efficiency make it a scalable solution for the rapidly changing FMCG sector [6] [7]. Furthermore, the "Adversarial Sparse Transformer for Time Series Forecasting" combines sparse attention with adversarial training to improve forecasting accuracy [8] [9]. Despite its promise, the iTransformer's simplicity may offer quicker adaptability for FMCG workflows. "Timenet: Temporal 2D-Variation Modeling for General Time Series Analysis" excels in capturing complex patterns but lacks the iTransformer's flexibility [11]. Lastly, "A Time Series is Worth 64 Words: Long-Term Forecasting with Transformers" explores transformers' potential for long-term forecasting, yet the iTransformer's architecture strikes a balance between long-term forecasting and nuanced understanding crucial for FMCG applications [10].

Building on the exploration of transformer models for time series forecasting in the FMCG sector, we now move into a crucial aspect of our research which is demand sensing—the integration of external factors such as social media data. This section highlights the importance and implications of leveraging external data sources to enrich demand forecasting models.

Building on our examination of transformer models for time series forecasting in the FMCG sector, we now move on to a critical part of our research: demand sensing—the incorporation of external variables such as social media data. This section emphasizes the value and significance of using external data sources to improve demand forecasting models. Utilizing social media data for demand sensing provides vital real-time insights into customer sentiments and developing trends, which are critical for FMCG companies to stay

competitive. F, Dachyar, M., Taurina, Z., and Qaradhwai, Y. (2021) emphasize the need of adjusting to quickly changing consumer behaviors [12] [13]. Social media platforms provide valuable consumer insights, boosting forecasts by collecting market trends and reactions to brand initiatives. Integrating social data improves predictive accuracy, enabling businesses to anticipate demand shifts and adjust output accordingly. However, the diversity of sources presents obstacles in data collecting and interpretation. Transformer models provide a robust solution capable of processing and integrating a wide range of data inputs, increasing the versatility and effectiveness of demand sensing systems [14].

In conclusion, the iTransformer model's unique approach to handling multivariate time series data, coupled with its computational efficiency and superior forecasting capabilities, justifies its selection as the optimal model for time series forecasting in the FMCG industry. Its comparison with models discussed in Table 1 describes its advantages in addressing the specific challenges of FMCG demand forecasting, making it a valuable tool for improving the accuracy and reliability of forecasting processes in this sector.

III. METHODOLOGY

Our research applies the iTransformer model for demand forecasting in the FMCG sector, aiming to enhance the performance over the existing LSTM model. We integrated client data, Google Trends, and social media data, ensuring alignment by week, year, product name, and country. This integration involved standardizing and incorporating sentiment scores from social media and customer reviews from platforms like Amazon, crucial for understanding product sentiment.

The datasets underwent rigorous cleaning to handle missing values, correct outliers, and normalize features, pivotal for the iTransformer model's effectiveness. Feature engineering included calculating rolling means and consumption rates, alongside competitor analysis via Google Trends data.

Model training involved selecting relevant features, tuning the iTransformer model to our dataset, and testing its efficacy against a TimesNet model, using metrics like MSE and MAE. This comparison helped refine our model by identifying performance gaps and areas for improvement.

For demand-sensing, five separate models were implemented, and the code was designed to choose the best model for the specific forecast for predictions. The five models implemented were Gradient Boosting, XG Boosting, Light GBM, Random Forest, and a stacking ensemble method of the four mentioned models. These models were compared using the RMSE (root mean squared error) and implemented in such a way that the best model for each forecast was chosen to perform the predictions. Training these models involves splitting the data into sets for training,

validation, and testing, using techniques like cross-validation to optimize hyperparameters and prevent overfitting.

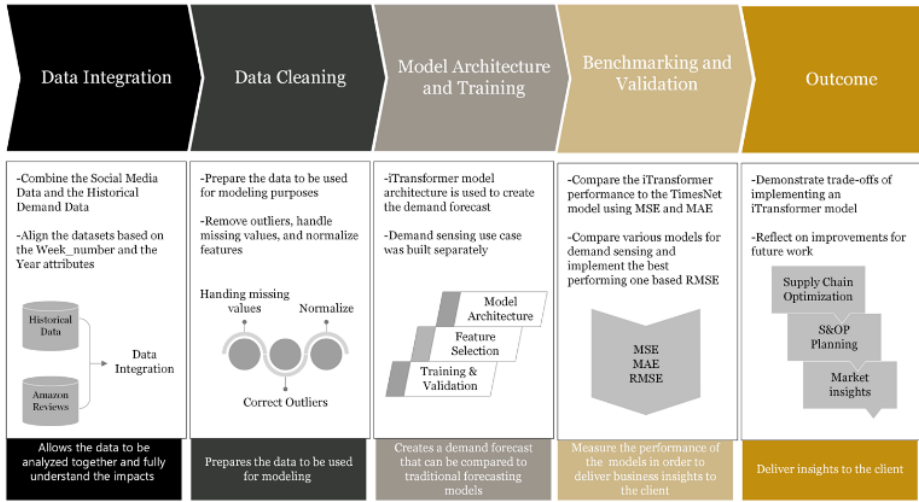
During the initial phases of training our iTransformer and TimesNet models with the client-provided datasets, it became apparent that the volume of data was insufficient to fully leverage the potential of these advanced transformer models. To address this limitation, we augmented our dataset size by a factor of 46, which significantly improved the models' training process. This experience underscores a critical insight into the operational requirements of transformer models: the substantial volume of data necessary to harness their predictive power effectively. In scenarios where data availability is constrained, the efficacy of these models may be compromised, highlighting a potential limitation in their application to small datasets.

To overcome the data insufficiency, we tested the architecture using the ETT-m1 dataset, providing insights into its ability to handle different data granularities and forecasting lengths. More details on the dataset used for iTransformer and TimesNet (Benchmark model for iTransformer) can be found in Table 9 in the Appendix.

and effectiveness. This allows for performance tuning and validation by comparing predicted values against actual outcomes. Further, testing these models against existing predictive tools can highlight potential improvements in accuracy and efficiency, making transformer models highly beneficial for enhancing predictive capabilities in supply chain and inventory management scenarios.

B. Google Trends Data

The Google Trends dataset, a vital tool for demand forecasting, records search interest over time for various brands along with data completeness, providing insights into consumer behavior patterns. An upward trend in searches often suggests a rise in demand, guiding businesses to adjust their production and inventory levels, while a decline may indicate waning consumer interest, prompting a reassessment of marketing tactics. The cyclical patterns captured by this dataset reveal seasonality and event-driven fluctuations in demand, enabling companies to optimize planning for these peaks, thereby maintaining robust brand health and consumer perception which correlates with demand levels.



Furthermore, analyzing Google Trends data in comparison to competitors can shed light on market positioning and unearth strategic opportunities by identifying strengths and areas for improvement. This data, when combined with other metrics such as sales figures, social media sentiment, and economic indicators, offers a comprehensive view of the market dynamics, substantially enhancing the precision of demand forecasts. The dataset's "isPartial" indicator helps distinguish between established trends and emerging patterns, allowing companies to quickly adapt to changing market

IV. DATA

A. Client Data

The datasets supplied by the client are organized into four main categories, detailed in Appendix B tables 2 through 5, and are designed to aid in the analysis of shipment and consumption metrics for specific brand products. These datasets are structured to support the training and testing of transformer models, which excel in processing sequential time-series data. With attributes like week numbers, years, product identification, and country information, these datasets provide the temporal and categorical context needed for forecasting future trends in both shipments and consumption.

Utilizing these datasets, transformer models can be trained to predict key outcomes such as shipment and consumption volumes, using historical data to gauge the model's accuracy

conditions and leverage real-time insights to capitalize on new opportunities or mitigate risks, making it indispensable for strategic planning in a competitive market landscape. Additional details on this data set can be found in table 6 of Appendix B.

C. Amazon Reviews Data

The dataset from Amazon reviews, as detailed in the data dictionary and comprising elements such as review titles, bodies, sentiment labels, and sentiment scores, offers invaluable insights for refining demand forecasting strategies. Beyond its obvious application in sentiment analysis, this data can crucially predict product demand by analyzing consumer reviews to understand preferences and trends. Businesses can identify key product features that resonate with customers, with positive reviews indicating strengths and negative feedback highlighting areas for improvement. Seasonal mentions and event-specific

comments within these reviews further guide predictions on when product demand might peak, aiding in more accurate planning and inventory management.

Sentiment labels categorize consumer feedback into positive or negative, providing an overview of market sentiment toward a product. This data, coupled with sentiment scores, allows for a nuanced, quantitative analysis of consumer emotions over time, enhancing the precision of demand forecasts. By correlating these sentiment scores with actual sales data, companies can craft sophisticated models to anticipate demand fluctuations based on evolving consumer sentiments. For instance, high sentiment scores often correlate with spikes in demand, signaling businesses to adjust their production strategies accordingly. Integrating these insights with traditional metrics like sales history enriches demand prediction models, equipping businesses with a comprehensive view of market dynamics and enabling proactive strategy adjustments in alignment with consumer demand trends. Further details about the dataset can be found in table 7 of Appendix B.

D. ETT-m1 Data

The Electricity Transformer Temperature (ETT) dataset, essential for the long-term functionality of electric power systems, incorporates high-resolution, 15-minute interval data over two years from distinct regions in China. Identified as part of the ETT-small collection, it comprises datasets from two separate stations, each labeled ETT-small-m1 and ETT-small-m2, reflecting the specific region of data collection. Each data set aggregates over a million observations per series, meticulously recording eight unique features that are pivotal for analyzing and understanding the operational dynamics of electrical transformers. These features encapsulate a detailed timestamp, the primary predictive measure of transformer oil temperature, and six additional variables indicative of various external power load characteristics, offering a comprehensive dataset for time-series forecasting.

This expansive dataset serves as a critical asset in training the iTransformer and TimesNet models, showcasing their capability to effectively forecast future scenarios based on intricate patterns and trends observed in historical data. The ETTm1 subset, specifically, with its seven-dimensional feature space and designated prediction lengths of 48, 96, and 192 intervals, which spans dataset sizes as mentioned in Table 9 Appendix B, ensuring a robust framework for evaluating the performance of advanced forecasting models. The frequent, 15-minute collection interval provides a granular view into the operational status and trends within the electric power system, enabling the iTransformer model to leverage its unique architecture for precise, long-term forecasting across a wide array of use cases within the sector. More details about the data and the attributes can be found in table 8 Appendix B.

V. MODELS

A. iTransformer Modeling and Architecture

The foundation of our research is the iTransformer, a special version of the conventional Transformer model created just for time series forecasting. The foundation of this model is the notion that the Transformer architecture's effectiveness in multivariate time series analysis can be significantly increased by reversing its dimensions, particularly in the Fast-Moving Consumer Goods (FMCG) sector.

The iTransformer distinguishes itself by encoding each time series as variable tokens and using the self-attention technique to detect multivariate relationships. This technique allows for a more sophisticated understanding of how different variables interact over time. Each variate is processed through a number of Transformer blocks, which include layer normalization and a feed-forward network, allowing for the extraction of complicated series representations from historical data.

Our decision to use the iTransformer approach stems from its proven ability to manage the erratic nature of the FMCG industry. Through the integration of external factors like competition analytics, sentiment analysis, and Google Trends data, the iTransformer offers a thorough framework for demand prediction.

1) Pros and Cons

The approach enhances forecasting accuracy and adaptability by effectively capturing the intricate dynamics of multivariate time series. Large lookback windows are well managed, and computational problems common to conventional models are avoided. There can be a severe learning curve because of the model's intricacy and the unique approach. Performance is strongly influenced by the caliber of the incoming data.

2) Tuning Parameters

The number of Transformer blocks (L), the dimensionality of the embedded tokens (D), and the self-attention mechanism settings are some of the important parameters that can be changed to maximize the performance of the iTransformer model. A compromise between forecasting accuracy and computing efficiency can be achieved by fine-tuning these parameters.

3) TimesNet as a Benchmark Model

TimesNet, a novel approach to time series analysis, shifts 1D time series data into a 2D space to capture temporal variations effectively. It utilizes multi-periodicity, transforming time series into 2D tensors and applying 2D kernels, which enhances its ability to model complex temporal dynamics. The TimesNet architecture features adaptive discovery of time series multi-periodicity and extraction of temporal variations through its TimesBlock module and inception block, providing a nuanced modeling of temporal variations.

B. Demand-Sensing Modeling

The FMCG industry is highly volatile, and demand forecasts can be influenced by external factors. For our study, we implemented various models using the external data that was collected from Google Trends and Amazon. This enabled us to measure the sentiment surrounding the brand and competitors utilizing a pretrained Transformer model DistilBERT from the PyTorch library. The Google Trends interest over time attributes described earlier were used to measure consumer engagement with that of the client and the competing brands. Companies often struggle to measure external influences on demand forecasts, but our approach offers a solution by using publicly available data. Using the actual shipment and consumption values 5 separate models were implemented: Gradient Boosting, XGBoosting, Light GBM, Random Forest, and an ensemble stacking method of the four models. These results are discussed later in the Results section.

1) Pros

The analysis process offers numerous advantages, including comprehensive data collection and preprocessing, demonstrated by meticulous web scraping and thorough preprocessing efforts, such as addressing missing values and encoding categorical variables. This foundational work ensures the data's quality and readiness for subsequent analysis and modeling, setting a strong basis for accurate insights. The use of a broad spectrum of regression models facilitates an extensive comparison of different algorithms, highlighting the multi-model approach's value in identifying the most suitable model for the data's characteristics. Additionally, the application of the Root Mean Square Error (RMSE) metric provides a quantitative basis for model comparison, while feature scaling enhances model performance, especially for algorithms sensitive to input variable magnitudes.

2) Cons

Although there are many advantages to our approach, the analysis would benefit from incorporating explicit model validation and overfitting mitigation strategies such as cross-validation or regularization to ensure models' generalizability to unseen data. While preprocessing effectively addresses many data issues, further attention to error handling and validation within the modeling phase is crucial for safeguarding against unexpected data anomalies, thereby enhancing the analysis's reliability. Moreover, the exploration of advanced models without corresponding hyperparameter tuning might not fully exploit these models' capabilities. Systematic tuning stands to significantly improve performance, underscoring the potential for optimizing model outcomes through careful adjustment of model parameters.

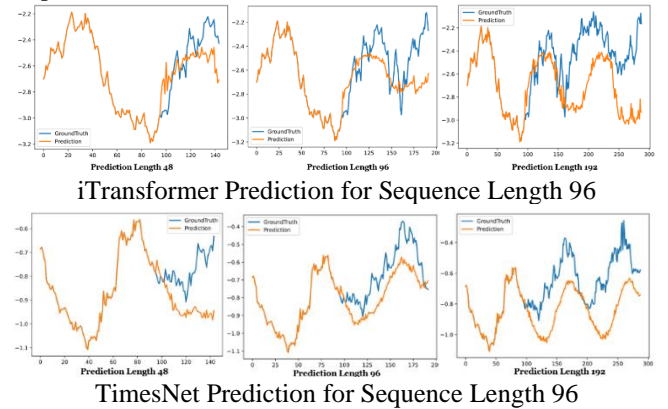
VI. RESULTS

A. iTransformer Results

The results of the iTransformer and TimesNet models, as applied to the ETTm1 dataset, are summarized in the table

and corresponding time series forecasts. For prediction lengths of 48, 96, and 192, the iTransformer consistently outperformed TimesNet, as evidenced by lower Mean Squared Error (MSE) and Mean Absolute Error (MAE) values across all prediction horizons. Specifically, the iTransformer achieved MSEs of 0.31299, 0.34189, and 0.38293 for the respective prediction lengths, whereas TimesNet produced higher MSEs of 0.46972, 0.54550, and 0.63605. Similarly, MAEs for the iTransformer were 0.35610, 0.37674, and 0.39570, compared to TimesNet.

The Graphs of the forecasted time series against the ground truth for both models further illustrate the iTransformer's superior performance. Notably, the iTransformer's forecasts are closer to the ground truth, especially for shorter prediction lengths, demonstrating its robustness and precision in modeling time series data. These results validate the iTransformer's efficacy in time series forecasting and underscore its potential in improving demand forecasting accuracy in the FMCG sector. The findings will be instrumental in guiding future model optimizations and implementations.



Dataset	Prediction Length	iTransformer		TimesNet	
		MSE	MAE	MSE	MAE
ETTm1	48	0.31299	0.35610	0.46972	0.49384
	96	0.34189	0.37674	0.54550	0.53269
	192	0.38293	0.39570	0.63605	0.57069

B. Demand-Sensing Results

The results of our demand-sensing modeling results provide insight into the effectiveness of utilizing different factors. Here are our top-3 performing models in terms of MSE:

Brand	Shipment			Consumption		
	Ensemble	Gradient Boosting	XGBoost	Ensemble	Gradient Boosting	XGBoost
Brand 1	3,196.67	3,290.58	3,440.99	3,430.34	4,298.22	4,749.20
Brand 2	15,834.61	15,322.67	16,890.92	11,768.22	12,841.09	15,788.81

Utilizing Google Trends and Amazon data, coupled with a pretrained DistilBERT model, the study evaluated the impact of public sentiment on demand forecasts for Brand 1 and Brand 2.

For Brand 1, the ensemble model yielded an MSE of 3,196.665 for shipments and 3,430.344 for consumption, indicating relatively precise predictions. Gradient Boosting reported slightly higher errors, while XGBoost had the highest MSE among the three evaluated models.

In the case of Brand 2, the MSEs were generally higher across all models compared to Brand 1. The ensemble model again performed the best for shipments with an MSE of 15,834.61 and for consumption with an MSE of 11,768.22. Gradient Boosting and XGBoost followed, with the latter showing the highest error rates again, indicating a trend consistent with Brand 1's results.

VII. CONCLUSION

In conclusion, this study successfully demonstrated the effectiveness of transformer models and demand-sensing techniques for demand forecasting in the fast-moving consumer goods (FMCG) industry. By leveraging the innovative iTransformer model and integrating external factors such as social media sentiment and competitive analysis, we significantly improved forecasting accuracy compared to traditional methods. The iTransformer's unique architecture and computational efficiency, paired with comprehensive sentiment analysis using DistilBERT, provided a robust framework for understanding market trends and consumer behaviors.

The results of this research highlight the potential of advanced analytics in enhancing demand forecasting precision, offering actionable insights for FMCG companies to navigate market volatility with increased confidence. The successful application of these models not only underscores their practical relevance but also opens avenues for future research to further refine and adapt these techniques to other sectors and industries, contributing to a broader understanding of advanced forecasting methodologies.

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APPENDIX A: LITERATURE REVIEW PAPERS

Table 1: Transformer Models Literature Review Comparison

Transformer Architecture	No of Layers	Challenges	Benefits	Loss Function
Informer	Informer contains a 3-layer stack and a 1-layer stack (1/4 input) in the encoder, and a 2-layer decoder.	Managing the computational complexity introduced by long sequences and ensuring the model's scalability and efficiency without sacrificing prediction accuracy.	Ability to handle very long sequences efficiently, its improved performance compared to existing models, and its innovative approach to reducing computational and memory requirements.	MSE
TFT	The number of layers in TFT is not specified explicitly, but the model architecture includes multiple components like gating mechanisms, variable selection networks, and several layers within the temporal fusion decoder, including sequence-to-sequence layers and multi-head attention mechanisms.	Ensuring interpretability without sacrificing performance. Complexity of integrating various input types	The ability to handle a wide range of forecasting scenarios with different types of inputs, and new forms of interpretability that offer insights into the temporal dynamics learned by the model.	Jointly minimizing the quantile loss summed across all quantile outputs:
AST	Encoder-decoder models consist of multiple layers in both the encoder and decoder, and the number can vary based on the implementation specifics. Discriminator is added	Managing adversarial training complexity and ensuring sparse attention accurately identifies relevant temporal dependencies	Improved forecasting accuracy, especially for long sequences, and enhanced model robustness	Combination of quantile loss for the generator (to capture the overall pattern of time series and align predictions with ground-truth) and adversarial loss (to regularize the prediction from a global perspective and improve sequence-level accuracy). This dual-loss approach leverages the benefits of both worlds: accurate step-level forecasting and global

				sequence fidelity.
PatchTST	The model experiments with varying the number of Transformer layers ($L=\{3,4,5\}$) and model dimensions ($D=\{128,256\}$), with the inner-layer of the feed-forward network being $2D$. This setup indicates a flexible architecture that can be adjusted based on the complexity of the time series data and the specific requirements of the forecasting task.	Model's adaptability to different types of multivariate time series data, Adjusting the model's parameters, including the number of Transformer layers and model dimensions, to optimize performance without overfitting or underfitting can be complex.	Reduced computational complexity, ability to learn from longer historical data, and enhanced representation learning capabilities.	MSE
tiTransformer	Model architecture does not specify the exact number of layers or parameters. It mentions the use of multiple Transformer blocks (TrmBlock) stacked together, each comprising layer normalization, a feed-forward network, and a self-attention module, suggesting a multi-layered approach	Adapting the Transformer architecture without modifying its core components for time series data.	Improved performance on time series forecasting tasks by effectively capturing multivariate correlations. Enhanced interpretability of the model's predictions due to the novel application of self-attention mechanisms. Flexibility and generalization capability, making it suitable for a wide range of forecasting applications.	MSE, MAE
TimesNet	Does not explicitly enumerate a total count of layers within the TimesNet model, it provides detailed insights into its architecture, highlighting the core component known as the TimesBlock.	Model complexity, computational resources, and the need for fine-tuning parameters to specific dataset characteristics	Good with mixed dataset performance. Results also verify the potential of TimesNet in performing as the general-purpose backbone for large-scale pre-training in time series forecasting.	MSE

APPENDIX B: DATA DICTIONARY

Table 2: Shipment Forecast Using Best Model

Column Name	Description
Week_number	Integer used to store the calendar week for the forecasted shipment
Year	Calendar year for the target variable
Product_name	String value for the product name of the specific brand
Product_ID	Unique number value for the product identification
Country	String value for country where the shipment is being forecasted
Forecasted_shipment_value	Numeric value that is the target variable and predicted shipment forecast

Table 3: Actual Shipment Demand

Column Name	Description
Week_number	Integer used to store the calendar week for the actual shipment
Year	Calendar year for the target variable
Product_name	String value for the product name of the specific brand
Product_ID	Unique number value for the product identification
Country	String value for country where the shipment value
Actual_shipment_value	Numeric value that is the target variable and actual shipment value

Table 4: Consumption Forecast Using Best Model

Column Name	Description
Week_number	Integer used to store the calendar week for the predicted consumption
Year	Calendar year for the target variable
Product_name	String value for the product name of the specific brand
Product_ID	Unique number value for the product identification
Country	String value for country where the consumption is being forecasted
Forecasted_consumption_value	Numeric value that is the target variable and predicted consumption forecast

Table 5: Actual Consumption Demand

Column Name	Description
Week_number	Integer used to store the calendar week for the actual consumption
Year	Calendar year for the target variable
Product_name	String value for the product name of the specific brand
Product_ID	Unique number value for the product identification
Country	String value for country where the consumption value
Actual_consumption_value	Numeric value that is the target variable and actual consumption value

Table 6: Google Trends Data – Over Time

Column Name	Description
Date	The date for the data point, typically weekly.

Brand Name	An integer representing the search interest for Brand on that date.
isPartial	A Boolean indicating whether the data for the given period is complete or preliminary.

Table 7: Amazon Reviews

Column Name	Description
title	The title of the review provided by the customer. It summarizes the customer's experience or opinion about the product.
body	The full text of the review written by the customer. It contains the customer's detailed experience, opinions, and comments about the product.
sentiment_label	A label indicating the overall sentiment of the review as interpreted by sentiment analysis algorithms. It classifies the sentiment of the review into categories.
sentiment_score	A numerical score that quantifies the sentiment of the review. The score typically ranges from -1 to 1.

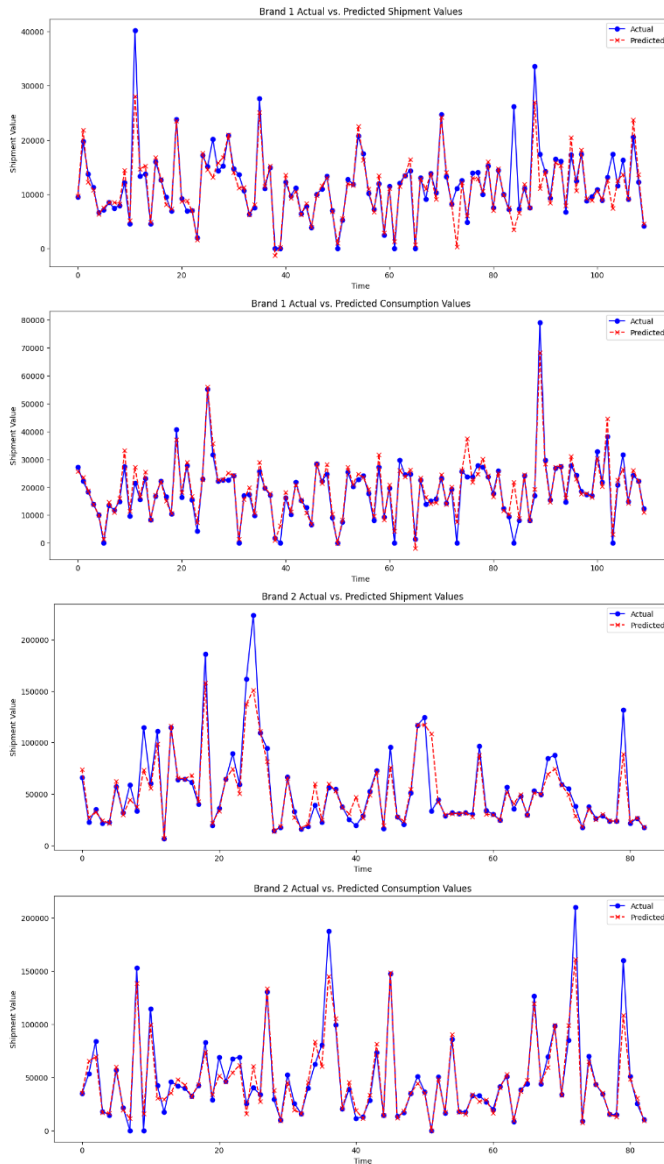
Table 8: ETTm1 Dataset

Column Name	Description
date	The recorded date
HUFL	High UseFul Load
HULL	High UseLess Load
MUFL	Middle UseFul Load
MULL	Middle UseLess Load
LUFL	Low UseFul Load
LULL	Low UseLess Load
OT	Oil Temperature (target)

Table 9: ETT-ml Overview

Dataset	Dimensions	Sequence Length	Frequency	Prediction Length	Dataset Split (Train, Validate, Test)
ETT-m1	7	96	15min	48	(34,417, 11,473, 11,473)
				96	(34,369, 11,425, 11,425)
				192	(34,273, 11,329, 11,329)

APPENDIX C: RESULTS



APPENDIX D: AI RESEARCH TOOLS

As part of our IP project, we tried an extensive literature review to anchor our research in the current scientific discourse on transformers and demand sensing. The sheer volume of existing literature initially seemed daunting. However, leveraging several AI tools transformed this challenge into a manageable, even enjoyable task. Here's a breakdown of the tools that were particularly instrumental to our success:

- Semantic Scholar:** Our first stop was Semantic Scholar. Its AI-driven search and summarization capabilities were invaluable. Not only did it help us find relevant papers quickly, but its smart summaries allowed us to gauge a paper's relevance without reading it in full. This tool was particularly helpful in narrowing down our initial pool of literature.
- Google Scholar:** Though not an AI tool, Google Scholar served as our gateway to the vast world of academic literature. Its powerful search algorithms helped us pinpoint research papers, theses, books, and conference papers relevant to our topic. What made Google Scholar stand out was its ability to show highly cited papers and the references within each article, providing us with a roadmap of influential works in our area of study. The simplicity of Google Scholar, combined with its depth of resources, made it an indispensable tool for our literature review.
- Scite:** Scite was helpful in assessing the reliability and impact of the papers we considered. Its unique approach to categorizing citations (supporting, mentioning, disputing) gave us a clear picture of the consensus around specific findings, which helped in refining our bibliography with authoritative sources.
- Connected Papers:** Understanding the relationship between different studies was crucial for our review. Connected Papers provided a visual representation of how each paper was related, helping us identify key papers and themes we might have otherwise missed. It was like having a map of the literature landscape, guiding us to crucial connections and insights.
- Zotero:** Managing our references was a breeze with Zotero. Its ability to automatically extract metadata and organize citations saved us countless hours. Moreover, Zotero's integration with word processors meant that formatting our bibliography was no longer a tedious task but a seamless part of our writing process.
- ChatGPT:** Whenever we hit a roadblock, whether understanding complex concepts or drafting sections of our review, ChatGPT was there to help. It provided quick summaries, explained methodologies, and even suggested how to structure our arguments. Though we always double-checked its outputs against primary sources, ChatGPT was like having an ever-present tutor guiding us through the process.
- PubTrawl:** This tool was particularly useful later in our review process. As we started synthesizing our findings, PubTrawl's AI-driven summaries and analysis helped us identify trends and gaps in the literature, ensuring our review was both comprehensive and insightful.
- Turnitin:** Before final submission, we ran our review through Turnitin. While primarily a plagiarism checker, it helped us ensure that all citations were properly attributed and that our work maintained academic integrity. It was the final step in our process, giving us confidence in the originality and rigor of our review.
- Claude.ai:** proved invaluable for quickly understanding complex texts and generating concise summaries, enhancing our efficiency in digesting vast amounts of research. Its AI-driven insights helped us identify key themes and draft parts of our review with greater ease.
- Typeset.io:** was instrumental in the final stages, simplifying the process of formatting our document according to academic standards. It ensured our review was professionally presented, with correctly formatted citations and references, saving us significant time and effort.