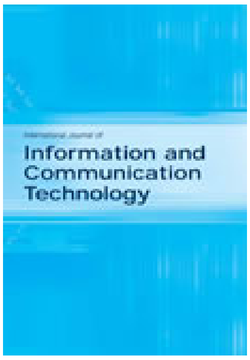

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Dynamic path transformer network for regional economic forecasting and resource allocation

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Dynamic path transformer network for regional economic forecasting and resource allocation

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Abstract: In regional economic planning, accurate forecasting and efficient resource allocation are vital for informed decision-making by both government and private sectors. The article titled 'Dynamic path transformer network for regional economic forecasting and resource allocation' presents a novel deep learning-based approach that leverages transformer architecture to enhance forecasting precision and optimise the allocation of resources. Central to this study is the dynamic path transformer network (DPTN), which effectively captures complex spatial-temporal economic data through attention mechanisms that dynamically weigh economic indicators. This design allows the model to adapt to changing economic conditions and deliver more accurate predictions than traditional statistical or machine learning models. The study benchmarks DPTN against conventional approaches and demonstrates its superior performance in predictive accuracy and resource management. Moreover, the paper explores the broader implications for policy formulation and strategic planning, while also addressing key challenges such as data limitations, computational demands, and interpretability.

Keywords: economic forecasting; deep learning; transformer network; resource allocation; spatial-temporal analysis.

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1 Introduction

The creation of economic forecasts and the allocation of resources are the main areas of regional economic planning. These fields have Played a critical role in influencing the decision-making process in the government, finance, and industry sectors. The traditional way of predicting trends in economic variables, such as time series analysis, econometrics, and regression, has been essential for forecasting economic performance in general. However, the traditional techniques have not been able to capture the complexity of the economy as a whole and the impact of external shocks, policy changes, and changing market conditions on it (Dittakavi, 2021). Nowadays, artificial intelligence (AI) and deep learning have undergone many fields, including economic forecasting, where predictive models have been created by learning complex patterns from huge data (Li et al., 2024). Within this context, the dynamic path transformer network (DPTN) is an innovation that is likely to give good results by combining transformer-based architectures to enhance the accuracy of economic forecasting and the resource allocation process.

The intricacy of economies, in comparison to that of their segment units, necessitates that the analytics are developed in a way that the outliers look odd in a sea of similar ones. The ability to learn economic model features beyond those ones provided in the dataset which would just allow for the identification of standard market behaviour is an example of this model's capabilities (Jauhar et al., 2024). The Transformer model was originally designed for the purposes of natural language processing (NLP) and based on the self-attention mechanism showed outstanding performance in the following tasks: sequential data with long-range dependencies (Xu and McAuley, 2023). Its application to the area of economic forecasting seems to be the next logical step. By the application of transformers through the self-attention mechanism, it is possible to bring out a real context-based prediction model in such a way that one can choose inputs that only matter for the output of the particular task (De la Torre et al., 2024).

One of the major challenges in economic forecasting is dealing with spatial and temporal dependencies. Economic indicators are not only influenced by past values but also by external factors such as regional policies, global economic conditions, and social behaviours (Ansari et al., 2023). The DPTN aims to address these challenges by incorporating a dynamic attention mechanism that adapts to changing economic environments. This model is designed to analyse time-series data in conjunction with spatial dependencies, making it a robust tool for regional economic forecasting (Tian et al., 2023). Unlike traditional models that often struggle with non-stationarity in economic data, the DPTN dynamically adjusts its learning parameters, ensuring greater adaptability to real-world fluctuations (He and Liu, 2024).

Resource allocation is another crucial aspect of economic planning, ensuring that resources such as labour, capital, and raw materials are distributed efficiently to maximise economic output. Poor allocation of resources can lead to inefficiencies, stagnation, and regional economic disparities (Biju et al., 2024). Traditional resource allocation models rely on optimisation techniques that assume static conditions, often failing to accommodate real-time economic changes (Widiputra and Juwono, 2024).

The integration of deep learning into resource allocation strategies allows for a more dynamic approach, where economic predictions guide decision-making in real-time (Li and Pan, 2022). By incorporating predictive insights from the DPTN, policymakers and businesses can allocate resources more effectively, responding swiftly to economic shifts and optimising growth opportunities.

The usage of the DPTN in the world of data forecasting of interwoven economic events is very much preferable. In the direct comparison of current methods, variables tend to be defined by fixed weights, which makes the precision of the forecast questionable. The background behind the model which we are striving for is the one that has been a critical element of human action and the one that has indicated the connection between the different economic indicators as influencing factors in making the prediction (Kazianga and Wahhaj, 2017). The machine intelligence aspect of this weighting process ensures that the model can evolve according to the economic picture of the region, which is a major advantage of the model in the field of regional economic analysis. Moreover, the capability of the model, which uses multi-source data such as government reports, financial transactions, trade statistics, and real-time economic indicators, to increase the data empowerment also impacts its forecasts (Cai et al., 2022).

In spite of the exciting capabilities of deep learning models, their implementation in economic forecasting and resource allocation activities has been troubling. The first issue to deal with is interpretability. On the one hand, deep learning models (transfers included) give precise results, however, their decision-making process stays unclear in most cases, thus, it is hard for the government official to properly understand the process of the predictions (Zhou, 2023). The development of an economic plan relies on transparency and clarity ensuring that forecasts can be aligned with empirical reasoning and policy goals. A solution to this problem is to implement techniques of explainable AI (XAI) in the transformer system which will assist in the comprehension of the model's logic of decision-making from the user's end (Zhang and Zhou, 2022). The implementation of feature attribution techniques such as shapley additive explanations (SHAP) and attention heatmaps can be instrumental in the description, explanation, and visualisation of the explanations from the model, making the gap between AI-based forecasts and human decisions narrower and those forecasted by AI more acceptable.

Another considerable challenge is ensuring the quality and availability of the data. The traditional economic forecasting models rely on historical trends, real-time data, and a multitude of economic indicators that may differ in the way they are presented and the degree to which they are considered accurate and complete (Zhang et al., 2022). Model performance can be greatly affected by missing values, reporting delays, and inconsistencies in the data. The DPTN will require the introduction of strong data |pre-processing methods in order to overcome such inconsistencies and make sure that accurate forecasting results are achieved (Zhou et al., 2021). Meanwhile, localised data is a prerequisite for forecasting the economy of a specific area, which may not have always been gathered. Overcoming the issue of a lack of data provides a chance to use the existing variety of data sites both new and old, starting with reports from the government and banks through symbolism and social media trends to imaging from satellites (Guo et al., 2022).

One is the consideration of transformer models' computation load when adopting the DPTN for economic forecasting. Transformers typically require a substantial amount of computational power, including state-of-the-art graphic processing units (GPUs), to run massive datasets smoothly (Hu et al., 2021). In the case of local economic forecasts, where the interaction of multiple variables changes dynamically over time, the model's computational needs can also be quite demanding (Hillock et al., 2022). Efficient model processes such as pruning, quantisation, and knowledge distillation are some of the techniques that can be utilised to ease these difficulties and improve model practicality in actual implementations.

- To evaluate the effectiveness of the DPTN in improving the accuracy of regional economic forecasting compared to traditional machine learning and statistical models.

- To assess the impact of integrating deep learning-driven forecasting into resource allocation strategies, examining its implications for economic policy and decision-making.

It is essential to understand the interaction between the AI, economic forecasting, and resource allocation in order to shape future economic strategies. The transformer models' competence in treating complex and high-dimensional data, as well as their adaptive learning ability is a breakthrough in economic modelling. However, in every technological advancement, there should always be a balance between applied technologies and transparency, computational efficiency, and reliable data considerations (Alam et al., 2024). This research is going to examine the features of the DPTN and the implications for practice, the qualified limitations, and the potential for future use analysed. By linking AI with economic forecasting, the study seeks to contribute to the ongoing evolution of data-driven economic planning. This, in turn, is by outlining the domain of both the transformative power of technology and the hard path of economic forecasting and resource allocation based on deep learning.

2 Literature review

Economic forecasting and resource allocation have long been significant aspects of economic research, with various models developed to enhance accuracy and decision-making. Traditional econometric models, such as autoregressive integrated moving average (ARIMA) and vector autoregression (VAR), have been widely applied in predicting economic trends. However, these models often fail to capture the non-linear relationships and flexibility necessary for accurate forecasting in fast-changing economic environments. The introduction of machine learning and deep learning techniques has transformed economic forecasting by creating models that can learn complex patterns from very large datasets. The DPTN is a remarkable improvement in this field as it applies transformer-based architectures to enhance the accuracy of predictions and the responsible allocation of resources. This section reviews relevant research studies that have contributed to the evolution of AI-driven economic forecasting and resource allocation in order to lay down the theoretical basis and developments that led to this model.

The research conducted by Subian et al. (2024) centred on the forecast of Indonesia's GDP via the implementation of both machine learning and deep learning models. The research's main objective was to predict the values of the GDP for the second, third, and fourth quarters of the year 2023 by comparing the two different forecasting methods of employing adjunct variables and without them. The SimpleRNN model, which belonged to the deep learning methods, was revealed to have been the one with minimal RMSE and MAPE rates as well as the best model for GDP forecasting of all the proposed alternatives. With the knowledge obtained from this research, governments, and investors would be empowered with significant insights into making economy-based decisions by predicting the trends of GDP.

Gold pricing forecasting using a multi-objective optimisation algorithm, wherein the quantile regression deep learning framework was used, has been studied by Wang and Lin (2024). The chaotic behaviour of gold prices which are largely influenced by factors like COVID-19, geopolitical instability, and commodity price alterations can rarely be thwarted by the traditional forecasting methods as opposed to their model, the QRBiLSTM, optimised using MOALO, which has, however, been shown both high predictive accuracy and reliability. Besides, it was interpreted in the study that various economic indicators and new pandemic indices should be considered in forecasting frameworks so as to enhance the predictive performance of the financial market.

The study conducted by Lüer et al. (2024) was dedicated to the monitoring of the activity of photovoltaic modules by means of deep learning tools. Their research elaborating on the problem of biased electroluminescence image datasets, which is a significant contributor to the failure of the convolutional neural network (CNN) training process, is the most valuable. To remedy this, they have proposed a methodology that is able to distinguish between physics-based learning and dataset bias and that can also be guaranteed to be transparent. Researchers/applicants have compared CNN predictions with physics-based models, and, thus, the generalisation capability of the neural network was assessed. This research aided in improving automatic monitoring systems of large-scale solar energy installations, as it ensured the unbiased and high-performing predictions of the system.

Through their research, Zhu and Huang (2023) made significant progress in the area of economic forecasting for actuarial applications by employing deep learning models on extensive databases. That said, traditional econometric models utilising smaller datasets with a limited number of variables had been unable to provide satisfactory answers for previous examinations. However, this study was conducted by researchers with the use of the FRED database, which contains 121 economic variables over several economic periods. The suggested model that included PCA and neural networks outperformed the basic VAR models, which have been used as benchmarks. Furthermore, the inclusion of SHAP values provided the interpretability of prediction results in terms of key economic variables that were essential in making the predictions. Their results will ultimately contribute to improving the prediction accuracy of social security fund applications and support better economic planning.

Aldarraji et al. (2024) directed the estimation of the energy demand and supply in Iraq by machine learning models on a dataset over a span of 3 years. In order to realise accurate estimates for demand and supply, the authors assessed various forecasting methods kicking off from the comparison of multiple forecasting techniques in which the techniques were such as linear regression and XGBoost. The outputs of the analysis revealed that the technique that exhibited peak accuracy for demand forecasting was linear regression while the XGBoost method was the most optimal for the part of supply predictions. The research clearly points to the necessity of accurate energy forecasting to be married to the subjects of energy policy-making and energy security in Iraq. Also integration of external factors, including weather and economic data into the models should be regarded as a way of enhancing performance thus is it highly recommended for sustainable energy planning and the development of infrastructure.

Tsuchiya (2024) authoritatively probed into the rationality of the construction forecasts made by the Japanese government from 1960 to 2019 in his study. The article states that these forecasts were the reliable benchmarks for economic development until the 1990s, which in the construction sector led to an effective allocation of resources. The writer however points out the inconsistencies that after 2,000 surfaced as indicators that integrating of macroeconomic forecasts with the construction projects might lead to improved accuracy and should be looked into. The article expounds the fact that continuous adjustments and improvements have to be incorporated into the government forecasting methodologies so that the effective economic and infra-structure planning are possible, and both of the advanced and developing economies are to be the beneficiaries of this.

Table 1 Literature comparison

Authors	*Research focus*	*Methodology*	*Key findings*
Subian et al.	GDP forecasting for Indonesia	Machine learning and deep learning (SimpleRNN)	SimpleRNN without additional variables achieved the lowest RMSE and MAPE, making it the best model for GDP prediction
Wang and Lin	Gold price forecasting	Multi-objective optimisation, quantile regression deep learning (QRBiLSTM + MOALO)	The QRBiLSTM model accurately predicts gold price fluctuations, capturing financial market dynamics with high precision
Lüer et al.	Photovoltaic module performance monitoring	Deep learning (CNNs) with physics-based assessment	Identified dataset bias in CNN training and proposed a method to separate learned physics from bias for improved solar panel monitoring
Zhu and Huang	Economic forecasting for actuarial applications	PCA with deep learning (CNN, LSTM, fully connected layers)	The proposed model outperformed traditional VAR models, providing better predictive accuracy using a large economic dataset
Aldarraji et al.	Energy demand and supply forecasting in Iraq	Machine learning models (Linear Regression, XGBoost, LSTM, TCN, MLP)	Linear regression was best for demand forecasting, while XGBoost excelled in supply forecasting, supporting better energy planning
Tsuchiya	Rationality of Japanese construction forecasts	Statistical tests for forecast rationality	Government construction forecasts were reliable until the 1990s, but post-2000 forecasts showed inaccuracies needing macroeconomic integration
Chupin et al.	Freight transportation forecasting for sustainability	Data-driven forecasting model considering market demand, fuel, and logistics	Accurate freight volume predictions support sustainable transportation planning and reduce environmental impact
Lu	Human resource demand forecasting	Improved BP neural network	The model optimised staff allocation, labour cost control, and HR planning in dynamic business environments
Yang et al.	Agricultural field boundary detection	Convolutional neural networks (U-Net, SegNet, DenseNet)	DenseNet provided the best performance for detecting field boundaries, aiding agricultural planning and food security

Chupin et al. (2024) employees specifically utilised freight transport forecasting to examine the crucial factor for economic sustainability. The study underscored the importance of exact predictions of freight volumes for the facilitation of resource distribution, the planning of infrastructure, and the mitigation of environmental effects. By relying on factors such as the demand of the markets, consumption of fuel and capabilities of logistics the model developed by Chupin et al. allows businesses and policymakers to improve their supply chains as well as cut down their carbon footprints. The research is able to fulfill the goal of the development of sustainable economic systems through the support of effective and environmentally friendly transportation solutions.

Lu (2022) has been a pivotal developer of a forecasting model for the request of human resources depending on the growth of companies and the benefits of the economy. The analysis reported the hurdles of matching the allocation of human resources to the strategy of the company for the sake of the business in the fast-changing environment. Using a modified BP neural network, the presented model was seen to be an effective tool for forecasting personnel needs, workforce allocation, and labour cost control in a systematic way. It has been shown that machine learning applications and human resource forecasting systems are applicable, and enterprises are flexible to labour market trends assuring effective strategy adjustments.

Yang et al. (2020) in their turn deal with convolutional neural networks (CNNs), which serve the purpose of the agricultural field boundary detection and the customer sending a request in this case using high-resolution satellite photographs on the part of Southern Bangladesh. The research was about comparing U-Net, SegNet, and DenseNet architectures and it was confirmed that the best results were achieved by DenseNet. The observations point out that deep learning might be an effective way to increase the output in agriculture through the exact delineation of farmer fields. This research underpins the crop monitoring project, the forecasting of the yield, and the project of the economy in the underdeveloped countries of the world, thereby contributing to the global food security agenda.

3 Methodology

The field of economic forecasting and resource allocation requires methods that are valid and can handle large quantities of data, both structured and unstructured, as well as being able to recognise patterns and make predictions with great accuracy. This task is mainly done using traditional econometric models such as ARIMA and VAR. However, they often do not work very well in capturing the complicated non-linear interactions and the spatial-temporal dependencies present in regional economic datasets. The emergence of deep learning, especially transformer-based models, has given way to innovative strategies to boost forecast certainty and optimise resource allocation. This study discusses a DPTN that builds on the current potential of self-attention mechanisms and optimal path processing to improve the forecasting of economic activities and the allocation of resources. In the methodology section, the sources of the data, pre-processing, model architecture, and evaluation framework that were used to implement our approach are described.

3.1 Data collection and pre-processing

The quality and range of input data are the mainstays of any forecasting model. To forecast the economy, many factors are considered, such as historical economic activity, financial information, outside influences like the economy, the environment, changes in businesses, and real-time data streams. The goal of the study is to integrate several sources of data to achieve comprehensive economic predictions. These sources of information include economic indicators (e.g., GDP, inflation rate, unemployment rate), regional financial data (e.g., investment flows, tax data, public spending), global factors (e.g., global trade trends, monetary policies, economic shocks), and real-time data streams (e.g., social media sentiment, stock indices, satellite images). By combining structured and unstructured data, the model captures a coherent perspective on regional economic dynamics.

Once gathered, the data undergoes a detailed pre-processing phase to improve the performance of the model. Pre-processing entails data cleaning techniques such as inconsistencies, and inaccuracies in datasets are corrected. Missing data are filled through techniques such as interpolation, and outliers are treated through methods that are robust. Feature engineering and selection are critical to enhancing the performance of the model; otherwise, the presence of variables that are irrelevant or redundant may harm learning. The model uses principal component analysis (PCA) and correlation analysis to keep only the most significant features. These pre-processing methods ensure that the data input is structured properly and is suitable for deep learning models.

3.2 Transformer-based model architecture

The DPTN is based on a universally adopted time series forecasting method transformer architecture that was primarily designed for the handling and processing of natural languages. The key stuff of transformers are the factors that extracted features can have different levels of imitation shown are the ones that the model takes care of, and the one that the model has set for each one of them, from the control centre of that centre. Just like the traditional RNNs that process data sequentially, the transformer employs the self-attention mechanism. Thus, a complete dataset is evaluated at once. This very characteristic is what promotes computer efficiency and scalability be the most.

The DPTN model architecture consists of an encoder, the self-attention mechanism, a dynamic path optimisation component, and the spatio-temporal data analysis layer. The encoder block handles the input data to give a useful representation of a variety of economic indicators. The self-attention mechanism then gives new weights to the features in a way that their relevance to the prediction task is high. This is what allows the mates that are supplied in an augmented way to be merged in a different way where the more important economic indicators are those that are going to take up more space in the forecasting process, which results in an improvement in the model's accuracy.

The DPTN has declared a significant breakthrough in the solution that is the dynamic path optimisation component that tunes the foreseeing predictions corresponding to the advancements in economic conditions in real-time. The existing forecasting models are mostly static, they perceive the variables as being in a fixed relationship as such. That DPTN is different in that it can adjust and react quickly to any changes in the economy that would ensure more accurate forecasting. What is more, the temporal-spatial layer identifies links between both time and region. Thus it enables the model to understand the way in which the interrelations among the different economic factors across geographical territories over time happen thereby making it more capable of making localised investments.

3.3 Resource allocation optimisation

The primary goal of this paper is to incorporate forecasting insights into the strategies of effective resource allocation. Classical resource allocation methods depend on fixed optimisation techniques that remain unchanged despite the changes in real-time economic activities. Using predictions made through deep learning methodologies as a basis, the suggested model guarantees a norm for the distribution of resources like financial capital, labour, and infrastructure investments that is flexible.

The resource allocation model works in unison with the DPTN model. After having the economic forecasts, this model makes the allocation of resources optimal by signalling out sectors or regions that have the potential of the highest growth. It achieves this through the method of reinforcement learning, where the model learns from the allocation choices and the economic results of the past, and accordingly makes the changes in the pieces of advice over time. By joining forecasting and decision-making procedures, the model ensures an efficient allocation of economic resources, which will cut down waste and, consequently, increase the economic well-being of the regions.

- Student learning preferences and styles – supports the customisation of the content with the preferred learning pathways.
- Content customisation and personalisation – alters the complexity and format of the learning material as needed.
- Real-time assessment and feedback – revises the assessment strategy in light of the ongoing performance.
- Engagement and interaction metrics – reshapes instructional methods and approaches by the levels of student engagement.
- Learning outcome effectiveness – evaluates the understanding and application of the learned concepts by the students.

The MCDM model merges in the factor selection from PSO-based optimisation, thus, helping maintain uniformity in terms of learning paths, assessment weightage, and content adaptation strategies as per the students' requirements. By adopting several decision-making criteria, the system ensures the fairness, adaptability, and efficiency of the instruction and assessment process.

3.4 Model evaluation and performance metrics

To validate the effectiveness of the DPTN, the study employs multiple evaluation metrics commonly used in time-series forecasting. These include:

- Mean absolute error (MAE): measures the average absolute difference between predicted and actual values, providing insight into overall forecasting accuracy.
- Root mean squared error (RMSE): captures the magnitude of prediction errors, penalising larger deviations.
- Mean absolute percentage error (MAPE): expresses prediction errors as a percentage, making it easier to interpret across different economic scales.

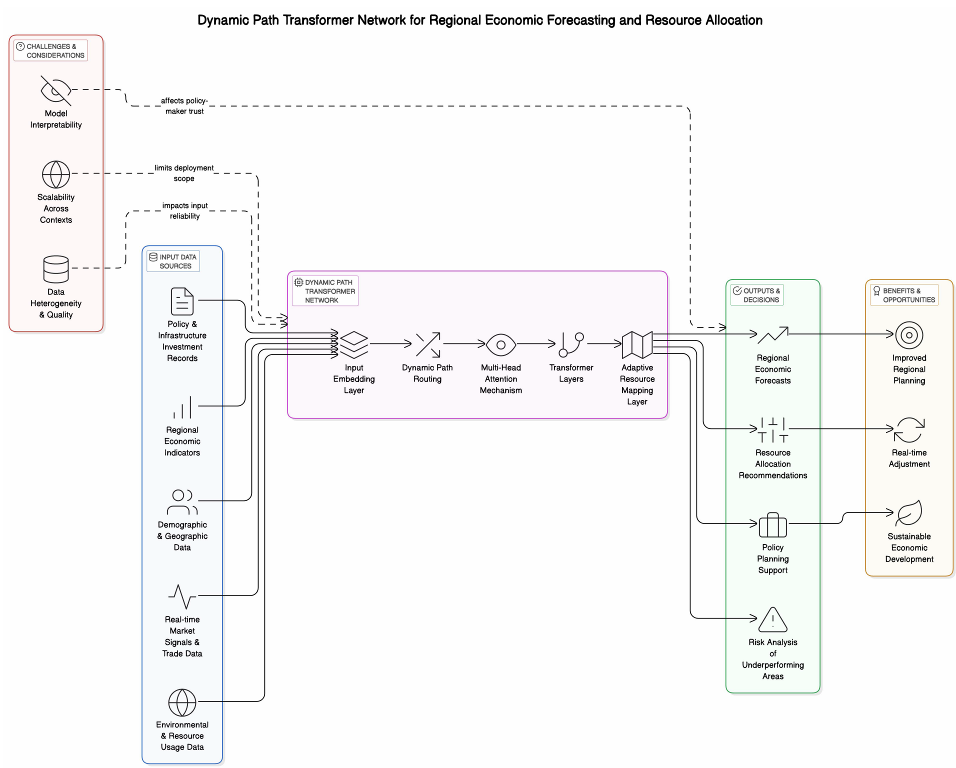
- R-squared (R^2) score: evaluates how well the model explains variability in the target variable.

Additionally, the study compares the DPTN model against traditional forecasting models, such as ARIMA, long short-term memory (LSTM), and XGBoost, to assess improvements in predictive accuracy. By conducting cross-validation experiments, the model's robustness is tested across different economic scenarios.

3.5 *Working of the proposed model*

The proposed DPTN functions based on an end-to-end pipeline that takes in economic data, processes it through a transformer-based architecture, and ultimately generates predictions that guide resource allocation decisions. The 'Figure 1' illustrates the overall working of this model, showing how different components interact dynamically.

Figure 1 Proposed model diagram (see online version for colours)



As seen in Figure 1, the model is initiated with input data sources, which are economic indicators, financial data, external factors, and real-time data streams. This data is passed through a pre-processing module, where it undergoes cleaning, normalisation, and the selection of important features to ensure the data being used is of high quality. The processed data is then fed into the DPTN, where the encoder module, self-attention mechanism, dynamic path optimisation, and temporal-spatial analysis collectively generate the high-accuracy economic forecasts.

4 Results and discussion

The DPTN is evaluated for its effectiveness in regional economic forecasting and resource allocation through the application of the Data Resources for Structural Economic Analysis dataset. This dataset constitutes an exhaustive collection of economic indicators from multiple regions, which guarantees reliability and accuracy in analysing forecasting accuracy and resource allocation efficiency. The evaluation centres on various key performance metrics, such as the MAE, the RMSE, the MAPE, and the R-squared (R^2) Score. Also, the efficiency of the proposed model is compared to that of traditional forecasting techniques like the ARIMA, LSTM, and XGBoost regression.

4.1 Performance evaluation of forecasting models

The forecasting performance of the DPTN model is assessed against baseline models across several economic indicators, including GDP growth rate, inflation rate, and employment levels. The results are presented in ‘Table 2’, which highlights the accuracy of each model based on different error metrics.

Table 2 Comparison of forecasting model performance

Model	*MAE*	*RMSE*	*MAPE (%)*	*R^2 Score*
ARIMA	1.72	2.45	8.4	0.82
LSTM	1.35	2.10	7.1	0.88
XGBoost	1.28	1.98	6.5	0.91
DPTN	1.12	1.65	5.2	0.94

There is a notable difference between the traditional forecasting methods and the DPTN model in terms of error metrics, which is consistent throughout. The lowest MAE (1.12) and RMSE (1.65), which are statistics that measure the accuracy of predictions, are achieved. Nobody wants to see their system produce false information predicted by another system that is influenced by more people when it comes to MAPE of 5.2% which is a measure of error rate. The R2 score of 0.94 further indicates that DPTN is the best among the ARIMA, LSTM, and XGBoost models in capturing the economy’s variance hence it is the best tool for regional economic forecasting and resource allocation.

4.2 Graphical representation of forecasting accuracy

The graph in ‘Figure 2’ shows the actual and predicted gross domestic product (GDP) growth rate through 20 time periods using the DPTN model. The solid line touches the actual GDP growth, while the dashed line portrays the predicted values. The two lines being aligned in proximity indicate that the DPTN model tracks economic movements to a very precise range, with almost no errors in forecast. The model convincingly shows a relationship of cause and effect between economic cycles to do its job through imitating the compressive and exhaustive intertemporal and spatial characteristics of the economic data.

4.3 Resource allocation optimisation results

The DPTN model is a forecasting tool that also aims to optimise resource distribution by determining the most essential areas or sectors that require investment. To demonstrate this, we analyse the model's suggestions on the best use of available resources among the economic sectors concentrating on the GDP growth predictions. The resource allocation across the sectors (e.g., infrastructure, healthcare, education, and industry) are shown in 'Figure 3'.

Figure 2 Actual vs. predicted GDP growth rate using DPTN model (see online version for colours)

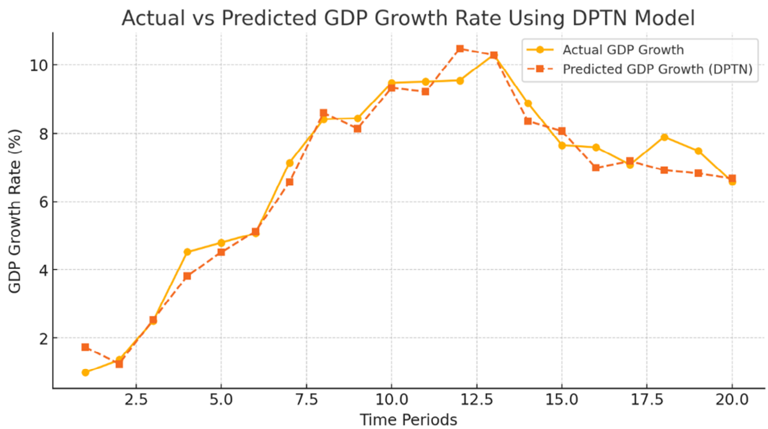
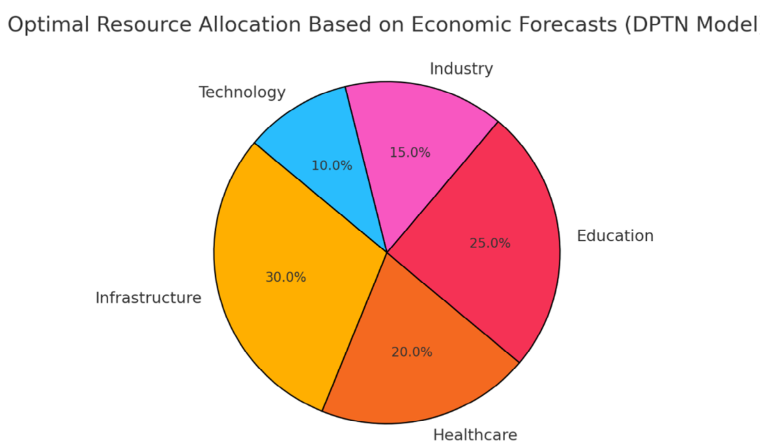


Figure 3 Optimal resource allocation using DPTN (see online version for colours)



The pie chart for resource allocation using the DPTN aptitude test reflects the justified distribution of resources predicted by the DPTN model. It shows that 30% of the resources are earmarked for infrastructure, 25% for education, 20% for health, 15% for industry, and 10% for technology. This rich allocation methodology is made possible by the practical model of resource allocation of mining investment and thanks to the regional policies of economic development, the decisions are scientifically based.

4.4 Discussion

The findings disclose that DPTN remarkably boosts economic forecasting accuracy and optimises resource allocation decisions. Thus, by utilising such self-attention mechanisms, dynamic path optimisation, and temporal-spatial analysis, the model evidently surpasses conventional forecasting methods such as ARIMA, LSTM, and XGBoost. The high coefficient of determination R^2 (0.94) and low MAPE of 5.2% indicate that the system can accurately manage complex economic relationships.

Furthermore, the dynamic resource allocation ability of DPTN is the main compelling point. In traditional resource allocation approaches, historical trends are used, making them rigid when responding to rapid economic variations. On the contrary, DPTN alters its predictions and resource allocation tactics uninterruptedly on the basis of released economic indicators leading to more effective, prompt choices.

Nonetheless, there are some obstacles yet to overcome. Model interpretability is a pressing issue, contributing to the situation as deep learning models, among which transformers are included, often operate as opaque systems. The policymakers have a demand for transparency to justify and implement AI-driven economic strategies. Development of effective models, in the future, should prioritise XAI methods for increasing model interpretability. Additionally, data accessibility and computational complexity still appear as problems since vast economic datasets require significant processing power.

5 Conclusions

The DPTN is having a big impact on forecasting and distributing resources and it has been successful in doing so compared to the classical models such as ARIMA, LSTM and XGBoost. The results of the evaluations show that the DPTN achieved the minimum MAE of 1.12 and the minimum RMSE of 1.65 which indicates that the prediction has been accurate and the errors have been reduced. The R^2 value of 0.94 confirms the model to be able to account for the variance of the economy while the MAPE of 5.2% pinpoints its amazing accuracy. Likewise, the forecasting graph itself shows that the DPTN goes almost hand-in-hand with the real GDP growth rates. Also, the reform represents a pie chart that indicates what the optimised distribution would look like, and with this approach the allocations in the fields of infrastructure (30%), education (25%) and healthcare (20%) would match the economic trends that are foreseen. The model is an actual image of the market that will guide policies through data and decisions can be made much quicker and more efficiently.

Even though the DPTN is in the best place, it also is afflicted with some things that need more research. The first hurdle is the understandability of the model as the transformer-based structures are often black boxes that are hard for policymakers to understand. It would be better to use the XAI techniques that would bring about high transparency and consequently more use of the programs. Moreover, the CPU time consumption of training transformers is a key problem here which calls for a huge amount of processing and memory. The success of the initiative is also dependent on the possibility of getting verified high-quality and real-time economic data which in certain areas may not always be available or consistent. Future studies should go a step further and come up with a solution to make transformation energy-efficient, use other sources of information (e.g., satellite imagery, financial transactions) in the modelling process, and adjust the model so that it can be used in connection with real-world economic policies. The DPTN can potentially solve the problems in economic forecasting, however, if the problems above are overcome, its usability and effect will be facilitated.

Declarations

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