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AI-Driven Economic Analysis: From Data to Decisions

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Abstract

This paper proposes artificial intelligence (AI) architectures for economic analysis, illustrating how AI components integrate from data inputs to decision outputs. Specifically, it reveals layered AI architectures, consisting of a data layer, intelligence layer, and decision layer, varying from traditional AI to generative AI and agentic AI, to address key economic analysis. This paper illustrates how economic data can be used in combination with AI and machine-learning models and applications to transform output into economic insights. It explores the transition from descriptive to predictive insights, from predictive to economic narratives, and from economic narratives to independent decisions. Moreover, it provides an economic evolution view on AI, starting with traditional AI, moving to generative AI and, finally, to agentic AI, and an economic intelligence transition from static analysis to creative modelling and finally autonomous economic reasoning. Furthermore, it develops country-specific use cases for AI-driven economic analysis, such as forecasting inflation and demand for electricity and gas, analyzing the impact of policy measures, and optimizing fiscal allocation in an emerging economy like Pakistan.

Keywords: Artificial Intelligence Architecture, Machine-Learning Models, Generative AI, Agentic AI, Economic Analysis.

JEL Codes: C5, C53, C52, C55

1. Introduction

Traditional economic analysis mainly uses complex theoretical models and econometric techniques in explaining economic behaviors of individuals and firms, forecasting macroeconomic and financial indicators, and informing policy decisions (Premavathi et al., 2025; Ogunbodede et al., 2025). Although these models and techniques have been fundamental to the advancement of economic knowledge, they are facing limitations in today's economic environment (Kumar, 2024). Moreover, these models are often built on strong assumptions, relationships, linearities, aggregated indicators, and limited or low frequency data, and are unable to account for the nonlinearity, structural breaks, behavioral heterogeneity, complex interactions of economic agents, and the rapid transmission of shocks across different markets and economies (García-García et al., 2025; Raj & Seamans, 2018). Furthermore, while traditional econometric models remain essential for theory-driven inference, they frequently fail to process high-dimensional data, to identify nonlinear relationships, and to provide timely insights needed for real-world economic and policy decisions (Blanchard, 2018; Acemoglu & Restrepo, 2018).

The digitalization of economic activity, however, has completely changed the economic data landscape, creating huge amounts of structured and unstructured data from various sources such as financial transactions, administrative records, satellite imagery, mobility data, online prices, and textual data from social media and news platforms (Agarwal et al., 2025). In addition to the traditional static sources of data, these real-time data sources offer the chance to observe economic behavior, dynamics, and sentiment that goes beyond traditional static frameworks (Einav & Levin, 2014). Thus, the attention of economists and policymakers has turned to addressing data scarcity, rather than focusing on data collection, toward the development of analytical architectures that could integrate, process, and transform a variety of data into timely, reliable, explainable, policy-relevant economic insights (Wan et al., 2025).

Artificial Intelligence (AI) has revolutionized the way in which economic analysis is done by automating the learning process from large, diverse, and high-dimensional datasets, identifying complex patterns within these datasets, and providing support for predictive, prescriptive, and interactive decision-making (Athey & Imbens, 2019; Hadfield & Koh, 2025). Machine learning and deep learning techniques are shown to provide great accuracy in forecasting and detecting nonlinearities between various economic variables, and large language models enhance analytical capacity by enabling automated text analysis, policy summarization, scenario generation, and interactive decision support (Korinek, 2023). Moreover, AI systems evolve to autonomous agents that can plan, reason, and act adaptively in complex economic settings (Korinek, 2025). But the ability to build a unified AI architecture, which encompasses data input, preprocessing, modelling, reasoning, and decision making is of greater significance to the impact of AI in the field of economics, as mentioned by Kalai et al. (2024) and Sarker (2022). The structural framework provided by a well-defined AI architecture provides the blueprint for everything from extracting insight from raw data to keeping AI systems scalable and easily adapted to changing economic conditions, with governance features for interpretability, transparency, bias management, and accountability (Krishnan, 2025). AI architecture consists of several layers, from data collection and preprocessing to intelligence and decision layers.

The paper proposes artificial intelligence (AI) architectures for economic analysis, illustrating how AI components integrate from data inputs to decision outputs. Specifically, it reveals layered AI architectures, consisting of a data layer, intelligence layer, and decision layer, varying from traditional AI to generative AI and agentic AI, to address key economic analysis. This paper illustrates how economic data can be used in combination with AI and machine-learning models and applications to transform output into economic insights. It explores the transition from descriptive to predictive insights, from predictive to economic narratives, and from economic narratives to independent decisions. It provides an economic evolution view on AI, starting with traditional AI, moving to generative AI and, finally, to agentic AI, and an economic intelligence transition from static analysis to creative modelling and finally autonomous economic reasoning. This paper provides country-specific application scenarios for economic analysis using AI, such as forecasting inflation and demand for electricity and gas, analyzing the impact of policy measures, and optimizing fiscal allocation in an emerging economy like Pakistan. In particular, the paper aims to introduce the architecture of AI for economic analysis as well as to develop country-specific use cases for AI-driven economic analysis with a focus on a developing economy such as Pakistan.

This paper is organized as follows: Section 2 gives an overview of the architecture of artificial intelligence in economics. Section 3 focuses on the application of artificial intelligence in economic analysis. Section 4 presents a case study on the application of artificial intelligence in the economic analysis of Pakistan. Section 5 concludes the paper.

2. Artificial Intelligence Architecture in Economics

In the field of economics, AI architecture can be used to analyze economic data, make predictions, gather economic intelligence, and design economic policies. AI architecture in economics involves using various components of AI to analyze, predict, gather economic intelligence, and design economic policies (Acemoglu, 2025). AI architecture is the structured framework of data, models, computational processes, and decision systems that are used to analyze economic phenomena and make policy decisions (Varian, 2019). It combines economic information (including macroeconomic data, microeconomic data, and even macroeconomic–microeconomic data), AI and machine learning models (prediction, optimization, simulation, etc.), and applications of converting the outcomes into economic information, including growth forecasting, risk assessment, and an evaluation of policy impact (Tao et al., 2024). It preserves the seamless integration of economic theory, empirical methods, and data in real time, enabling scalable, transparent, and context-aware economic analysis and decision-making.

A different perspective on the conceptualization of AI architecture in economics is an evolving sequence of computational layers, which enable economic analysis, policy design, and decision making. Architecture, moving from traditional AI to generative AI and to agentic AI, becomes more autonomous, adaptive, and consistent with real economic agents' behavior. Each approach contributes in different ways to economic modelling and develops comparable sets of facts, calculations, and governance.

Traditional AI architecture in economics is mainly analytical and predictive. It is mainly used to model, forecast, and analyze economic outcomes with structured data. (Athey & Imbens, 2019). It is used widely in the field of GDP and inflation forecasting, credit scoring, poverty targeting, tax compliance, and market risk modelling, enhancing the accuracy of forecasts, simulations of policy choices, better allocation of resources, and credit and market risk analysis. Its main issues, however, are a lack of reasoning, adaptability, and language comprehension, which makes it largely human-driven. Generative AI architecture represents an advancement in content creation and economic reasoning, aiming to generate text, scenarios, explanations, and synthetic data to support economic analysis (Korinek, 2023). It is used for policy drafting, scenario and counterfactual analysis, synthetic microdata generation, and research assistance. It also plays a co-creative role by generating policy briefs, reports, and simulated economic outcomes. (Mo & Ouyang, 2025). Agentic AI architecture represents a further advancement toward autonomous decision-making and adaptive policy systems. Its core purpose is to continuously act, reason, and learn within economic environments (LeCun, 2022). Its applications include adaptive monetary policy support, automated market regulation, dynamic pricing, crisis early-warning systems, and multi-agent market simulations.

Figures (1, 2, and 3) provide layered economics-focused AI architectures for traditional AI, generative AI, and agentic AI, comprising data layers, intelligence layers, and decision layers for key economic analysis.

The traditional AI Architecture in economics is based on classification, estimation, econometric inference, prediction, and optimization of structured data. Typically, the architecture starts with gathering data from sources such as national accounts, financial statements, surveys, and administrative records. Structured data covers macroeconomic indicators (GDP, inflation, interest rates, and unemployment), micro-level data (household surveys and firm-level data), and financial market data. The data is preprocessed by cleaning, normalizing, and seasonally adjusting, detrending, and normalizing, are processed using feature engineering, lags, growth rates, and indices are added to the data to make it suitable for use in modeling.

The modern machine learning and deep learning techniques are combined with traditional econometric techniques in the modeling layer. Econometric models like linear regression, vector autoregressive (VAR), and panel data models are used for inference and interpretation of structure. Machine learning models, like random forest, gradient boosting, classification algorithms, and optimization algorithms, help to predict and capture non-linear relationships. Long short time memory (LSTM) and transformer architectures are examples of deep learning models that are useful for long-horizon time-series forecasting. Causal AI models help to estimate the counterfactual outcomes to evaluate policy. Training and validation of models are done with careful procedures designed for time-series economic data to ensure reliability in the use of the models for policy analysis. The inference and analytical layer comprises pattern recognition, data classification, relation estimation, and prediction, like GDP growth, inflation, unemployment, credit risk, etc. The model results are then translated into economic decisions and policy recommendations. The outputs are passed on to a decision layer for policymakers, regulators, and firms, with macroeconomic dashboards, policy simulation & scenario analysis, and forecast reports as key elements. This architecture is mostly analytical and manual, with human economists having a significant role in the model building, setting of assumptions, and interpretation.

Generative AI Architecture in economics builds on the traditional AI framework to produce new economic content, like literature, scenarios, and policy drafts. It contains unstructured information, such as news articles, research papers, and policy documents, and structured economic information. The representation layer embeds textual and numerical data into a common semantic representation, such as time-series embeddings, panel data encodings, and text embeddings, enabling the model to capture context, narratives, and implicit economic relationships. The core foundation model layer contains large language models, other generative models like VAE or GAN, or diffusion models, which can learn deep patterns from economic text and data and produce logical economic reasoning, scenarios, and synthetic data. These foundation models are then fine-tuned using data from a particular domain, such as macroeconomic reports, econometric studies, and policy documents, to make the model outputs relevant to the context of economic theory, institutional frameworks, and regions, especially for policy-oriented applications. The inference layer enables counterfactual analysis, policy simulations, and scenario building. The model outputs are then translated into economic decisions and policy recommendations. The outputs are passed to policymakers, regulators, and firms in the decision layer. The generation layer generates policy briefs, scenario stories, synthetic datasets, and explanatory economic insights.

For economic applications of AI, explainability tools, or explainable AI (XAI) techniques, help to translate the outputs that are generated into understandable economic insights and narratives. These tools identify explanations, assumptions, and constraints in line with theory. The results obtained are checked with the known economic relations, past data, and theoretical expectations. Ethical checks involve issues of bias, data leakage, fairness, and using policies responsibly. AI systems are trusted and used according to regulations, since they are supervised by the human person in the loop. These are necessary for the responsible governance of the economy via AI. This architecture enables machines to learn from large-scale economic data to produce economic insights, forecasts, simulations, and policy narratives.

In the field of economics, Agentic AI Architecture is a step further in the evolution of analysis and generation towards economic decision making systems that operate without human intervention and can achieve specific goals. The systems designed within this framework are expected to function and evolve independently and adaptively in dynamic economic environments like markets, regulatory regimes, or policy contexts. It continually analyzes different economic scenarios with real-time data streams, including market prices, administrative data, macro indicators, and behavioral and sentiment signals. The raw economic data is translated into representations in the form of trends, expectations, risk signals, constraints, etc. The tools used, such as feature extraction, embedding, and time-series encoding, give agents the ability to develop beliefs regarding the economy, such as uncertainty and incomplete information, which are essential characteristics of real-world economies. The reasoning and planning layers combine LLM with reinforcement learning, causal inference, and game-theoretic approaches to assess, analyze, and predict trade-offs and consequences; to predict the analysis and response of the opposing side; and to plan a series of actions. Agents think about choices at the decision making level, applying their economic reasoning. Tools like reinforcement learning and causal inference can help the agents optimize economic goals, while respecting economic constraints and rules. The agents reason strategically about other economic players' responses by interacting with them, thus capturing strategic behavior. Agents make decisions at the action layer in a simulated or actual economic system. Actions can involve modifying policy recommendations, simulating interventions, and implementing policies. Agentic AI systems continually adapt their behavior based on the results or feedback that they receive. The feedback and learning layer evaluates outcomes, revised beliefs, models, and policies, and makes adjustments as time goes on. It is essential for agents to be able to adapt to this kind of feedback, as it allows them to adjust to shocks, such as a financial crisis, supply disruptions, or policy changes, in a volatile or uncertain environment. It is a very similar architecture to theoretical economic agents and is very useful for adaptive policy analysis and complex market modelling.

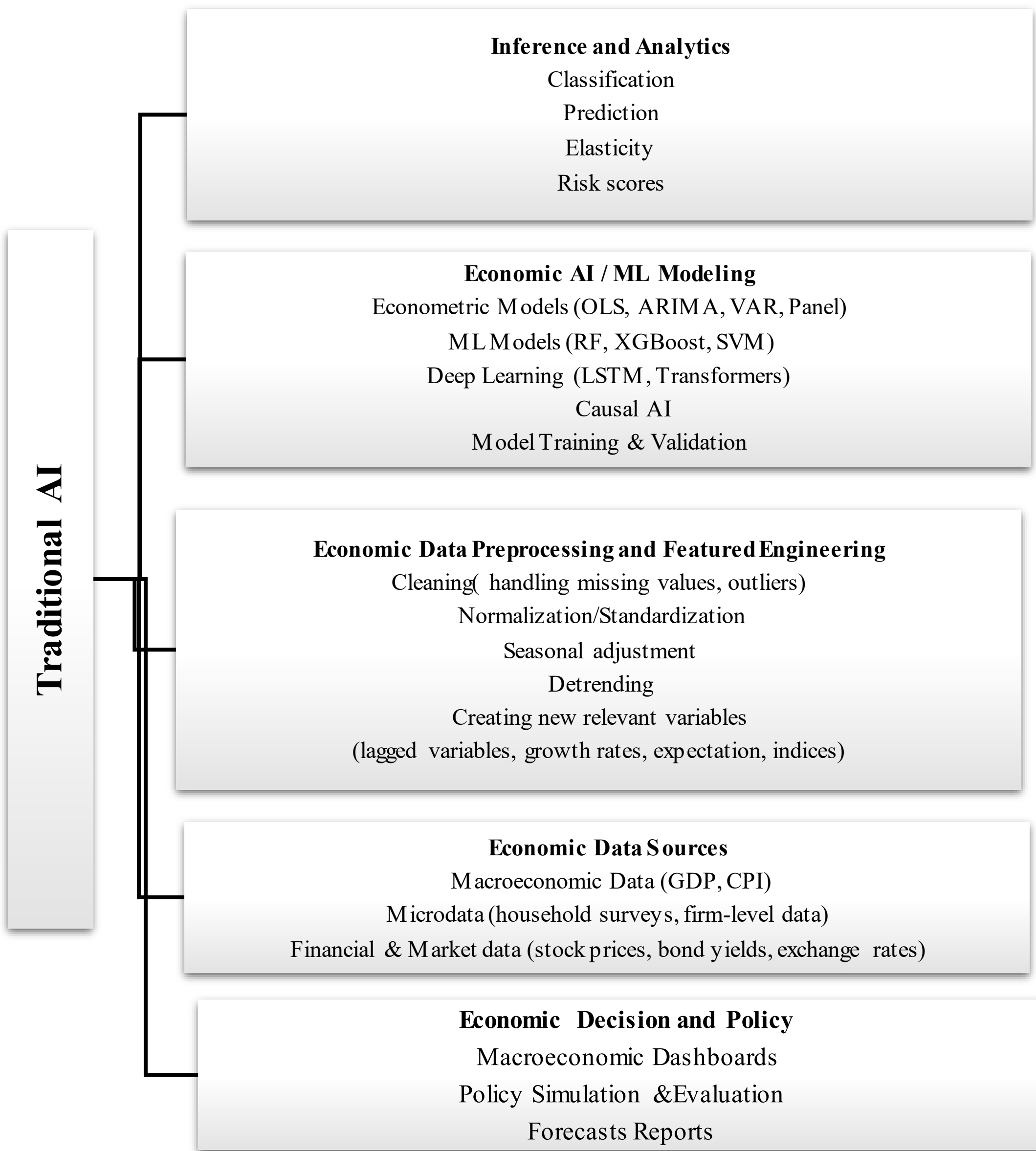

Figure 1: Traditional AI Architecture

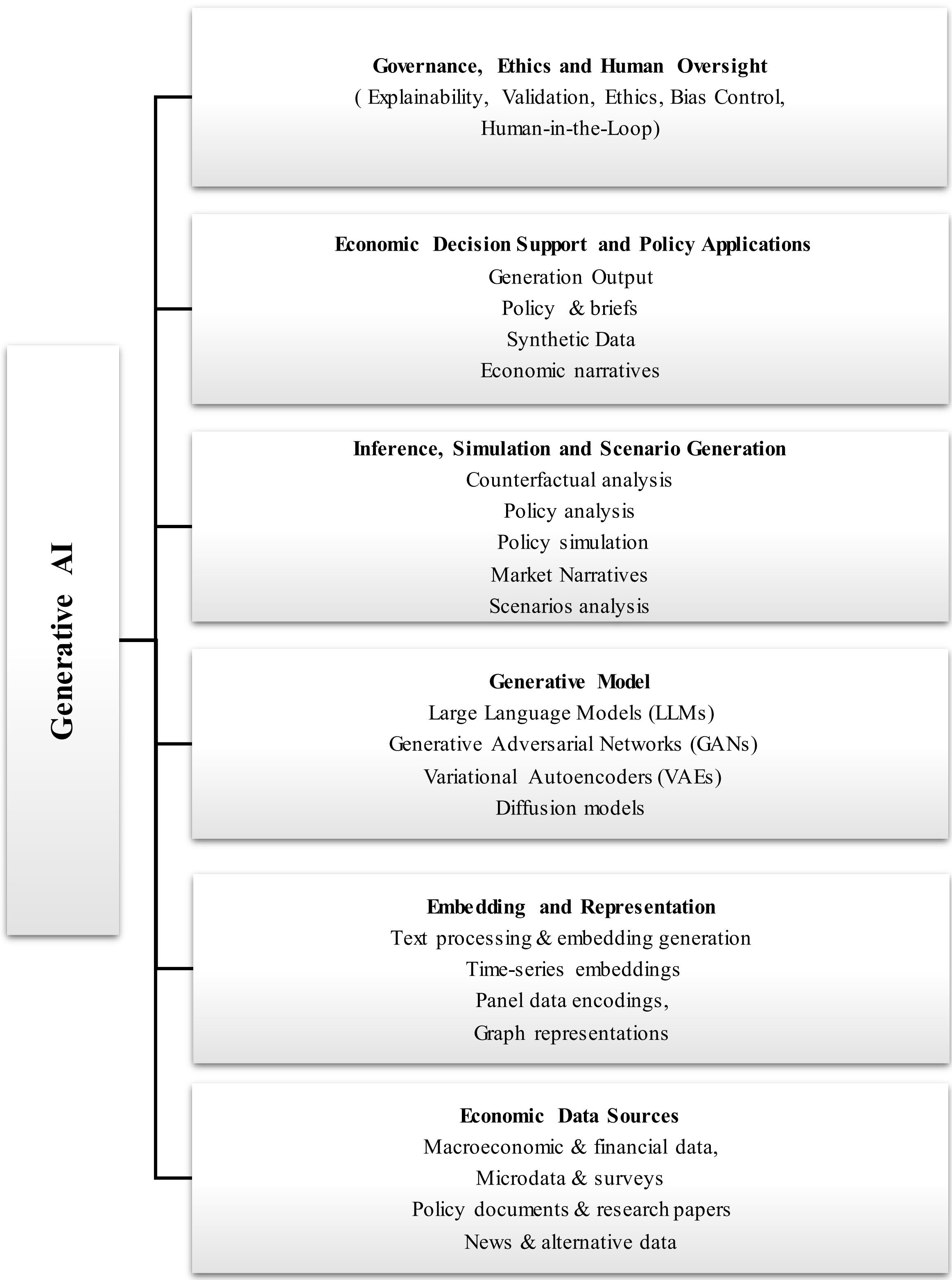

Figure 2: Generative AI Architecture

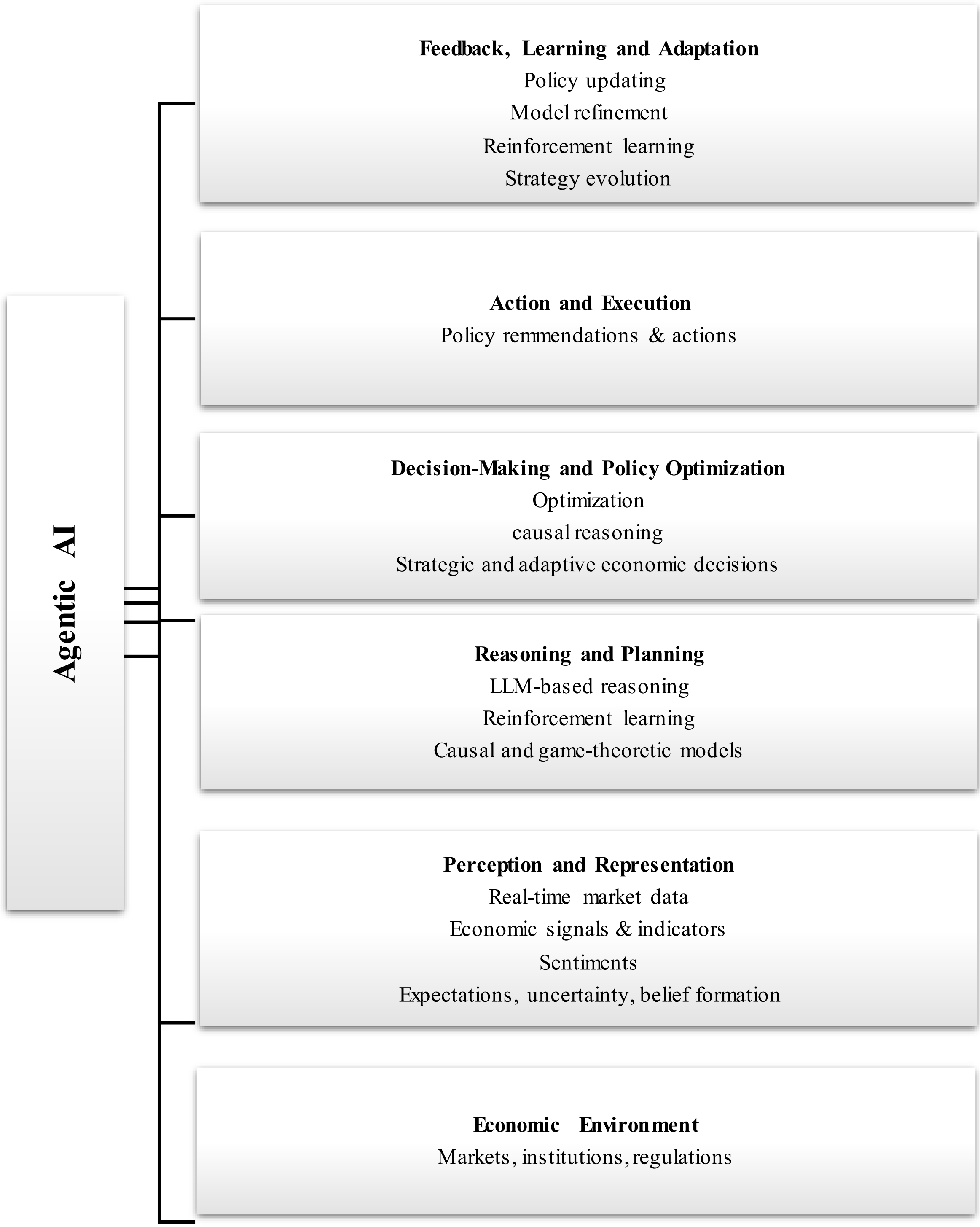

Figure 3: Agentic AI Architecture

3. Artificial Intelligence in Economic Analysis

AI for economic analysis relates to the use of AI methods to enhance data collection and analysis, model construction and theory testing, economic policy planning and decision-making (Wan et al., 2025). AI is transforming economic analysis with its ability to analyze data that is large-scale, complex, and real-time, as well as the speed and accuracy it provides (Tao et al., 2024). Economists are able to identify complex patterns and relationships that are often hard to detect using conventional analytical techniques by using AI to evaluate vast amounts of structured and unstructured data, or "big data" (Kumar, 2024). Machine learning techniques can find patterns, trends, and relationships that are non-linear and not considered by traditional econometric models. Machine learning models are able to improve the prediction of important macroeconomic variables like GDP growth, inflation, unemployment, and exchange rates based on past data and adjust to changes as they happen. This enables more rapid and precise economic insights, especially during times of economic volatility or change (Athey, 2018; Agrawal et al., 2022).

Artificial Intelligence (AI) can boost the accuracy of predictions, complementing the use of traditional econometrics in economic modelling and forecasting. The models that are built using artificial intelligence are much better at predictions as they learn from previous data with minimal assumptions, while traditional models focus on causal inference and theory-driven relationships (Athey & Imbens, 2019). Neural networks, random forests, and ensemble models are increasingly used to forecast GDP growth, inflation, exchange rates, and volatility of the financial markets. However, there are interpretation problems with these methods, and in order to ensure the meaningful interpretation of the policy, AI predictions need to be combined with an economic theory.

AI is crucial when it comes to assessing and analyzing policies. Governments and central banks use AI to ensure adherence to laws and regulations in taxation and spending, predict economic shocks, and to model the effects of policymaking. AI-based microsimulation models support evidence-based policymaking by helping policymakers assess the impact of monetary and fiscal policies at a ‘micro’ level of income groups and geographical areas. In developing countries, AI-driven analysis can support the identification of vulnerable populations in targeted social protection programs, making them more effective (Zhang & Li, 2025).

AI enhances microeconomic and sectoral analysis by deepening understanding of consumer behavior, the dynamics of firms, and the structures of the markets. AI models can be used to predict demand, fine-tune pricing, and model supply chains, while AI can help regulators identify collusion, market manipulation, and anti-competitive behavior (Gao et al., 2024). This dual application underscores the importance of AI in improving market efficiency and boosting regulatory supervision, as detailed by Wan et al. (2025).

For effective use of AI in economic analysis, it is essential to combine the use of AI tools with economic theory, reliable econometric methods, and solid governance structures. AI can enhance the quality, detail, and relevance of economic analysis, leading to better, more informed economic policy.

4. Case Study: Artificial Intelligence in Economic Analysis of Pakistan

In recent years, AI has emerged as a valuable tool for enhancing economic analysis, particularly when it comes to handling vast amounts of information, using sophisticated algorithms, and adapting learning capabilities. This case study explores how AI can be implemented or is being implemented in economic analysis to enhance the Pakistani context.

4.1 Use Case 1: Inflation Forecasting using Econometric AI Modeling

Inflation forecasting for Pakistan is based on monthly data from January 2000 to December 2024, using an econometric AI model.

i. Define the Forecasting Objective

- Policy objective: Forecast monthly CPI inflation
- Target variable: Headline CPI inflation (% MoM)
- Forecast horizon: 3, 6, and 12 months ahead
- Data frequency: Monthly
- Sample period: January 2000 – December 2024 (300 observations)

ii. Economic Framework (Theory-Driven)

A theory-based approach is used to predict the inflation dynamics in the context of Pakistan, which incorporates the most important macroeconomic channels that are identified in the economic literature and provides theoretical consistency as well as economic interpretability. In the monetary theory of inflation, excess liquidity in the economy is observed in money growth. The constant expansion of money due to the government borrowing from the central bank and the banking sector leads to a rise in the price level, according to the classical and monetarist theories of inflation. The exchange rate channel indicates that depreciation of the exchange rate of the PKR increases import prices, which eventually impact the domestic price level, putting stress on the BOP and exchange rate adjustment. This means that exchange rate fluctuations are an important factor in inflation volatility. The interest rate channel indicates that when the interest rate goes up, there is a decrease in economic activity and inflation, and when the interest rate goes down, there is an increase in economic activity and inflation. The channel highlights the effect of the central bank's policy rate on the rate of inflation and the demand-driven pressures on inflation.

iii. Data Collection

Table 1 provides a description of the variables that affect inflation and macroeconomic dynamics in Pakistan. Headline inflation can be defined as CPI inflation. M2 growth is an indicator of money supply growth. The monetary policy stance is reflected in the policy rate. The exchange rate of PKR against USD is indicated by PKR/USD. International oil prices are given in USD per barrel.

Table 1: Variable Description

Variables	**Frequency**	**Source**
CPI Inflation (%)	Monthly	Pakistan Bureau of Statistics (PBS)
Money Supply (M2) Growth (%)	Monthly	SBP
Policy Rate (%)	Monthly	SBP
Exchange Rate (PKR/USD)	Monthly avg	SBP
Oil Prices (USD/barrel)	Monthly avg	Trading Economics

iv. Dataset Construction

The final dataset is built as a well-balanced time series of monthly observations from January 2000 to December 2024, making it easier to perform economic and AI-based analysis. It comprises 300 monthly observations that reflect long-term trends, cyclical fluctuations, and a number of structural episodes in the economy of Pakistan. The dependent variable is inflation, and a comprehensive list of explanatory variables is included as listed in Table 2.

Table 2: Example (Illustrative)

Month	CPI (%)	M2 (%)	Policy Rate (%)	PKR/USD	Oil Price ($)
Jan-2000	3.9	8.1	11.0	52.1	27
Jan-2010	13.3	15.4	12.5	84.6	78
Jan-2020	12.6	9.8	13.25	154	64
Dec-2024	23.4	12.1	22.0	285	83

v. Data Preprocessing

The missing observations are filled by linear interpolation. Price level variables are transformed using logarithmic transformations. Key variables are transformed into growth rates and first differences to capture short-run dynamics and minimize persistence, such as changes in CPI (ΔCPI), money supply (ΔM2), and exchange rate (ΔER). Lastly, the stationarity test is performed using the Augmented Dickey-Fuller (ADF).

vi. Model Selection

For capturing short-run inflation dynamics and long-run structural relationships, the models are estimated on monthly data for the period 2000–2024 for Pakistan. An ARIMA model can be used for modeling inflation persistence, for analyzing the influence of past inflation on current inflation, and for generating short-run baseline forecasts.

A VAR system can be employed to obtain the joint dynamics of inflation, money supply, and exchange rate. The VAR model is suitable for the monetary transmission mechanism as well as pass-through analysis of the exchange rate because all variables are endogenous variables and can interact with each other and have a feedback effect.

Multiple Linear Regression (MLR) can be used to explicitly relate inflation to important explanatory variables like money growth, exchange rate changes, and interest rates.

Baseline Regression Model:

$$\pi_t = \alpha + \beta_1 \Delta M2_t + \beta_2 \Delta EX_t + \beta_3 Oil_t + \beta_4 PolicyRate_t + \varepsilon_t$$

where π_t is the rate of inflation, $\Delta M2_t$ denotes money growth, ΔEX_t is a change in the exchange rate, Oil_t is the oil price, and ε_t is the error term.

vii. Model Training (Estimation Period)

- Training sample: 2000–2020
- Validation sample: 2021–2024

Estimated coefficients in Table 3 illustrate the key forces driving inflation dynamics in Pakistan and are in line with economic theory. The coefficient of money supply growth is positive and high (0.45), thus once again confirming that excess liquidity and money supply growth have a strong inflationary effect. The exchange rate coefficient (0.33) suggests that depreciation of PKR/USD would increase prices of imports, resulting in a corresponding increase in the prices of domestic commodities. International oil prices also display a positive impact (0.21), which reflects cost-push inflation, as this inflation is passed on via energy prices, transport prices, and industrial input prices. The policy rate has a negative coefficient (−0.28), indicating that contractionary monetary policy has a negative inflationary impact by reducing aggregate demand, the supply of credit, and inflationary expectations.

Table 3: Estimated Coefficients (Illustrative)

Variable	**Coefficient**	**Sign**
M2 Growth	+0.45	Inflationary
Exchange Rate	+0.33	Strong pass-through
Oil Prices	+0.21	Cost-push
Policy Rate	−0.28	Disinflationary

vii. Model Validation

A rolling window forecasting framework is used to evaluate model performance as it enables parameters to be re-estimated over successive sub-samples and reflects changing inflation dynamics in Pakistan's dynamic economic setting. The accuracy of the forecast is evaluated by the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE), which are robust measures against large forecast errors and average forecast errors, respectively. For example, RMSE = 0.9 and MAE = 0.7. To observe the stability of the model, test it around important events of the economy and exogenous shocks, such as the global financial crisis in 2008, the IMF stabilization program in 2018, the climate-induced floods in 2022, and the adjustment of exchange rates in 2023-24.

ix. Inflation Forecast

AI-based inflation forecast model for 2024 uses data on macroeconomic variables for the year 2024. The model projects CPI inflation within the 24-26 percent range during the next six months, while M2 growth at 12 percent, the PKR/USD exchange rate at around Rs 285, international oil price of around USD 85 per barrel, and policy rate of 22 percent suggest that inflation persistence despite monetary policy tightening efforts depends on external and structural factors as well.

x. Use of policy by SBP

The analysis suggests that tightening the monetary policy stance is needed when forecasted inflation is projected to be above the threshold. When that occurs, it is recommended to increase policy interest rates to curb excess demand, ease inflation expectations, and minimize the effects of cost-push shocks or depreciation of the real exchange rate in the future.

However, the recommended policy adjustments are reversed if the forecast indicates a stable or near stable level of inflation in or near the tolerance range. The gradual monetary easing is necessary if the inflationary trends continue to decline. This forecast-based approach ensures that interest rate actions remain aligned with inflation dynamics and the macroeconomic stability objectives, fosters a forward-looking monetary policy stance, and boosts the credibility of the monetary policy stance.

In sum, the application of Econometric AI in inflation forecasting helps bolster evidence-based monetary policymaking in Pakistan while maintaining transparency, interpretability, and alignment with economic theory.

4.2 Use Case 2: Demand Forecasting of the Electricity and Gas Sector Using Deep Learning

Demand Forecasting of the Electricity and Gas Sector is based on historical consumption data using deep learning models such as LSTM and GRU networks.

i. Define the National and Operational Objective

- Objective: Forecast the short-term and medium-term demand for:
  - Electricity (MW load forecasting)
  - Natural gas (MMCFD consumption)

- Institutions involved:
  - Electricity: NTDC, DISCOs, GENCOs
  - Gas: SNGPL, SSGCL

- Policy relevance:
  - Load-shedding management
  - Fuel import planning (LNG, furnace oil)
  - Capacity expansion decisions
  - Tariff and subsidy design

ii. Energy Demand Drivers

The factors affecting the energy demand of the country are economic, policy, climatic, and seasonal, affecting consumption of energy in the form of electricity and gas. The rate of energy demand varies according to economic factors like changes in production and industrial closures, etc. The revisions in energy tariffs and the load shedding schedule of gas supply influence the consumption behavior directly through energy usage incentives and availability. This is driven, in part, by the sensitivity of the economy to the weather - very high temperatures during the summer season led to high electricity demand, and low temperatures during a cold spell led to high gas demand. Demand for the same product is also affected by seasonality because of religious, social, and agricultural cycles. Occasions like Ramzan and Eid holidays cause a change in the energy consumption of households and businesses, and agricultural seasons cause an increase in electricity demand because tube wells are in operation during these seasons.

iii. Data Collection

The variables that affect energy demand in Pakistan are shown in Table 4. Electricity demand is expressed as an hourly megawatt (MW) load, reflecting short-term load fluctuations, the peak demand characteristics, and the consumption patterns of regions. The daily gas consumption in MMCFD includes fuel for power generation, industry, and domestic consumption. Temperature and humidity are important exogenous factors because electricity and gas consumption are significantly influenced by extreme heat or cold. Behavioral and institutional changes that affect the timing of industrial activity and consumption are calendar effects that include public holidays and the month of Ramzan. Energy demand is linked to underlying economic activity and business cycles through economic indicators, including industrial output. Consumers' response to a price change is reflected in the change in electricity prices and gas tariffs. Supply constraints include outages and curtailments.

Table 4: Variable Description

Data Category	**Variables**	**Source**
Electricity Demand	Hourly MW load	NTDC / DISCOs
Gas Consumption	Daily MMCFD	SNGPL / SSGCL
Weather Data	Temperature, humidity	Pakistan Meteorological Dept
Calendar Data	Holidays, Ramzan	Government
Economic Indicators	Industrial output	PBS
Pricing Data	Electricity & gas tariffs	NEPRA / OGRA
Supply Constraints	Outages, curtailments	Utilities

iv. Dataset Construction

Table 5 shows a sample of data for electricity demand for an hourly time series and key climatic, temporal, and pricing variables. On 01-06-2024 at 14:00, the electricity load is observed as 24,500 MW, the temperature is 42°C, and humidity is 35 percent in extreme weather conditions. During the summer peak hours of 1500, the temperature is raised to 43°C and the humidity progressively reduced to 33 per cent, with the electricity load having increased to 25,200 MW, showing the sensitivity of electricity demand during such peak hours in summer in Pakistan. The tariff is fixed at 35, so any changes in demand can be attributed mainly to weather and diurnal demand (usage) variations.

Table 5: Electricity Demand Dataset (Hourly)				
Time	**Load (MW)**	**Temperature (°C)**	**Humidity**	**Tariff**
01-06-2024 14:00	24,500	42	35%	35
01-06-2024 15:00	25,200	43	33%	35

v. Data Preprocessing

Data preprocessing starts with a systematic approach to the handling of missing data. All continuous variables are measured on different scales, load, temperature, and tariffs are all z-scored. Dummy variables are used to encode categorical and institutional effects, for example, a signal for weekends or public holidays indicates whether or not there are changes in commercial and industrial activity, and an indicator for Ramzan signals whether or not there were changes in consumption patterns during hours of fasting. The cleaned and encoded data are converted into sequences of fixed-length windows in order to be able to predict future demands. The data is finally split into training, validation, and test sets to ensure not only powerful learning of the model, but also an unbiased evaluation of the model's performance out of sample.

vi. Model Selection

In this regard, several deep learning architectures are proposed to forecast the energy demand in Pakistan. Long short time memory (LSTM) networks are good at capturing the long-term seasonal effects, such as summer and winter demand cycles. Gated Recurrent Unit (GRU) models are a more efficient way to train a model for large utility datasets where faster training and lower memory usage are essential.

vii. Model Architecture

The sequence-based architecture of the electricity demand forecasting model is developed to capture both short-term power consumption patterns and longer-term temporal relationships. These inputs are processed through stacked LSTM (Long Short-Time Memory) hidden layers, which are well-suited to time-series data because they capture nonlinear relationships and preserve information over time; dropout is used within these layers to promote generalization and reduce overfitting. For system operators and policymakers, the output layer subsequently generates forecasts of the electrical load for the following hour or day, enabling for both short-term planning and real-time operational decisions.

vii. Model Training

The model training process should guarantee the accuracy and generalization of forecasting electricity demand. The loss function is the Mean Squared Error (MSE), which means that the larger the prediction error, the higher the penalty, and which is suitable for a continuous load forecasting scenario where a large error at peak periods is more significant. The Adam optimizer is used to efficiently update model parameters, which has the advantages of adaptive learning rate and momentum, resulting in faster and more stable convergence. The model is trained using multi-year historical data to allow the model to learn the long-term seasonal patterns, structural changes, and repeated patterns of demand driven by weather, economic activity, and calendar effects. To prevent overfitting, in which the model performs well on the training set but poorly on the test set, early stopping is implemented by watching the validation loss and stopping the training process when the loss on the validation set stops improving, thus making the model more robust and reliable for deployment in real applications.

viii. Model Evaluation

A wide range of performance metrics are used to evaluate model performance, both in terms of accuracy and robustness. The Root Mean Squared Error (RMSE) gives a more interpretable measure of the average error between the forecast and actual load, and highlights larger forecasting errors, especially at peak load times, while the Mean Absolute Error (MAE) emphasizes larger forecasting errors. Mean Absolute Percentage Error (MAPE) gives an error of forecasts in percentage terms so that it can be compared between different levels and time horizons of demand.

ix. Demand Forecast

Table 6 shows the difference between actual and predicted energy demand, and demonstrates the accuracy of the forecasting model in varying seasons and in different energy supplies. The model predicts the load of 25,700 MW during a peak hour in the summer when the electricity demand is at 26,000 MW, owing to extreme heat and high cooling demand. This is a relatively small deviation, which is indicative of good response to high stress situations on the power system.

Likewise, the actual consumption of 1,250 MMCFD for winter gas demand comes very close to a forecast of 1,220 MMCFD, a sign of the model's learning of a seasonal heating pattern and fuel consumption behavior. All in all, the limited differences between the actual and the forecasted values show that the model is able to reproduce the dynamics of electricity and gas demand. The errors from deep learning models are usually 15-30% less than the errors from traditional methods.

Table 6: Energy Demand Forecast

Period	Actual Load	Predicted Load
Peak Summer Hour	26,000 MW	25,700 MW
Winter Gas Demand	1,250 MMCFD	1,220 MMCFD

x. Operational and Policy Use

Energy demand forecasting is crucial for effective planning in the gas and electricity markets in Pakistan. It facilitates supply-demand matching, optimization of generation, cost minimization, and other decisions, such as imports of LNG. Forecasting also helps to inform infrastructure investments, supports tariff policy making (by OGRA and NEPRA), and helps in better integration of renewable energy in the grid without compromising grid stability.

4.3 Use Case 3: Inflation Impact Analysis on Households in Pakistan Using Generative AI Model

Inflation impact analysis on households is based on household level and macroeconomic data using a Generative AI model.

i. Define Objective

To analyze, explain, and simulate the effect of inflation on income groups, provinces, and urban-rural households in Pakistan to design targeted and equitable inflation mitigation policies by the Government of Pakistan, SBP, and social protection agencies.

ii. Economic Context

High prices of food items (wheat, rice, pulses, cooking oil, etc.), fluctuations in energy prices for fuel, gas, and electricity, and depreciation in the exchange rate and indirect taxes have been responsible for the persistent and volatile inflation in Pakistan. The overall CPI as reported by Pakistan Bureau of Statistics (PBS) masks significant differences in the variations in inflation experience among households. The impact of inflation is felt by low-income households, daily wage earners, and groups with fixed incomes more intensely than it is by other groups, owing to their consumption patterns, income vulnerability, and regional price variations, which means that a higher percentage of their budget is spent on food and energy.

iii. Data Sources

Household-Level Data

- Household-Level Data. Household Integrated Economic Survey (HIES – PBS)
  - Household income
  - Monthly spending on the category
  - Urban–rural classification
  - City or town of residence
  - Poverty status

Example:

Food is a significant share of bottom 20% households' budgets (55-60%)

- Top 20% spend 25–30% on food

Price and Inflation Data

- CPI & CPI Sub-Indices (PBS)
  - Food inflation
  - Furniture, building, water, electricity, gas
  - Transport (fuel)
- Weekly Sensitive Price Indicator (SPI).
- Utility tariffs (NEPRA, OGRA)

Example:

- Food inflation: +35% YoY
- Electricity tariffs: +40% YoY
- Petrol prices: +25% YoY

Income & Social Protection Data

- Wage growth data (PBS, SBP)
- BISP / Ehsaas beneficiary data
- Minimum wage levels

Example:

- Nominal wage growth: +12%
- Inflation: +28% → Real income loss: −16%

iv. GenAI-Based Analytical Framework

a. Data Integration

Generative AI integrates structured datasets, semi-structured data, and unstructured data. The structured datasets include the Household Integrated Economic Survey (HIES) and the Consumer Price Index (CPI), which provide data on income, expenditure, and inflation. The semi-structured data includes district-level price information, which provides data on the cost of living. The unstructured data includes open-ended household survey responses, grievance records, and consumer complaints. Large Language Models (LLMs) process this diverse information by converting household-level records into economic embeddings that numerically encode patterns of consumption behavior, price sensitivity, and susceptibility to inflation shocks.

b. Household Segmentation

Generative AI segments households into groups that are policy relevant and meaningful by applying learnt economic embeddings, based on similarities in income sources, consumption patterns, and price shock exposure. For instance, in Table 7, the urban low income, rural agricultural, and salaried middle-class household segments.

Table 7: Example Segments

Segment	Food Share	Energy Share
Urban Poor	58%	12%
Rural Poor	63%	6%
Middle Class	38%	15%

c. Inference, Simulation & Scenario Generation

Household-Specific Inflation Basket Generation

LLMs generate Pakistan-specific consumption baskets.

Example:

Urban Poor Household Inflation Rate = (0.58 × Food Inflation 35%) + (0.12× Energy Inflation 40%) + (0.30 × Other Inflation 15%)

Effective household inflation ≈ 30–32%

d. Inflation Impact Analysis

Generative AI converts household-level data into predictive economic risk indicators to evaluate the impact of inflation. GenAI estimates real income erosion by integrating localized pricing changes, CPI, and nominal income data, changes in consumption capacity by analyzing shifts in expenditure patterns, substitution behavior, and budget constraints, and poverty transition risk by identifying households that are likely to fall below the poverty line due to sustained price pressures or income shocks.

For example, consider a household earning a monthly income of PKR 35,000. At the current rate of inflation, Generative AI estimates an inflation-adjusted loss of PKR 8,500 per month, thereby creating a significant loss of real income. This decrease necessitates a decrease in food, health, and education consumption by the household.

e. Inflation Shock Simulations

Generative AI can simulate the effects of policy-relevant shocks to determine the differential impacts on household groups. A food inflation shock is equivalent to a loss of real income of 6.2% for the urban poor households and 3.1% for middle-class households, respectively, as their food expenditure burden is relatively high compared to the food expenditure share of the other classes of households. Thus, a 20% increase in electricity prices would have a larger effect on urban renters who are more dependent on electricity supply from the formal grid, compared to rural households, who are less dependent on the formal grid for electricity supply in scenario B.

f. Policy Scenario Generation

Generative AI can create other possible scenarios to test the effects of various policies. At the time, for instance, an additional PKR 3000/month to BISP would have been able to support 45-50% of the loss in income as a result of inflation for the poorest 20% of the population, which would have provided tangible support to the poorest households. Similarly, the immediate impact of a particular wheat subsidy would be to reduce food inflation exposure by 8-10 percentage points, directly reducing the impact on food spenders whose spending is significant on staple food.

g. Generative Output

The Generative AI framework generates a number of useful outputs, such as insights used for policy, as well as understanding complex economic data and turning it into insights that are relevant to policy. It produces household-level "inflation exposure indices" to reflect how much a household is exposed to inflation, taking into account its consumption patterns, income level, and local market conditions, etc. This micro-level information is aggregated to produce province/district-wise vulnerability maps that highlight economic stress geographic hotspots. The framework also includes estimates of real income losses for each quintile of income, which help to understand the impact of inflation on low-income and middle-income people. Furthermore, it provides interactive dashboards to keep track of the situation on the ground and guide economic interventions for policymakers.

V. Policy Impact for Pakistan

The insights generated using the GenAI framework can provide guidance to develop more informed and evidence-based policies across different areas. The system can help to identify the households and regions most vulnerable to inflation, which would enable more focused social protection interventions such as BISP and Ehsaas to reach the poorest and most vulnerable. Similarly, consumption patterns and price sensitivity are taken into consideration in energy and food subsidy reforms to enable policymakers to redesign energy and food subsidy reforms in an equitable and financially sustainable way. Lastly, the framework can precisely quantify vulnerability and exposure, which will help to reduce fiscal leakage during unforeseen price hikes and enable Government resources to be effectively and efficiently deployed to ease the economic struggle.

4.4 Use Case 4: Optimizing Fiscal Allocation in Pakistan Using Agentic AI Models

Optimizing fiscal allocation in Pakistan is based on fiscal and macroeconomic data using Agentic AI models.

i. Set Fiscal Objectives and Fiscal Constraints

The agent formalizes Pakistan's fiscal goals

- Fiscal deficit ceiling: ~6–7% of GDP
- Public debt: ~75–80% of GDP
- Debt servicing: ~50–55% of total federal expenditure
- **Policy objectives:**
  - Reduce poverty (≈ 39% of the population is multidimensionally poor)
  - Control inflation (≈ 20–25% CPI in recent years)
  - Development spending (PSDP ≈ 3% of GDP))

ii. Agentic AI-Based Analytical Framework

a. Data Collection and Integration

The agent ingests multi-source data, including:

- Revenue data
  - FBR tax collection (e.g., PKR 9.3 trillion target vs PKR 8.8 trillion actual)
- Expenditure data
  - Current expenditure (≈ PKR 14–15 trillion)
  - Development expenditure (≈ PKR 3–3.5 trillion)
- Macroeconomic data
  - GDP growth (≈ 2–3%)
  - CPI inflation (food inflation > 30%)

  - Exchange rate (PKR volatility)
- Social data
  - BISP beneficiaries (~9 million households)
  - Education spending (~2% of GDP)
  - Health spending (<1.5% of GDP)
- Climate risk data
  - Flood-prone districts (e.g., Sindh, South Punjab, Balochistan)

b. Forecasting Revenue and Expenditure

The agent uses machine learning models to improve fiscal monitoring by forecasting revenue and expenditure and adapting to changing macroeconomic conditions. On the revenue side, it forecasts the elasticity of sales tax with respect to inflation and estimates the growth of income tax in a GDP slowdown. On the spending side, it expects to spend more on debt repayments as a result of interest rate increases and estimates subsidies if there is an energy price shock. For example, a potential loss of revenue of PKR 400 – 500 billion exists, and the pressure of subsidy on energy is around PKR 600 billion.

c. Estimating Sectoral Returns

Agent estimates economic and social returns per PKR spent. Table 8 reveals the relative economic and social returns per rupee of public spending, showing distant variations in effectiveness across sectors. Low poverty impact (0.5-1.0) and large output response (1.4-1.6) of infrastructure investment are attributable to the employment and connectivity gains. Spending on education and health also has considerable effects, 1.2–1.5 for education and 1.3 for health, which contribute to the high and persistent poverty reductions resulting from human capital accumulation and productivity gains. Energy subsidies do, however, have an inefficient effect of 0.4-0.6 and a small impact on poverty due to leakage to higher-income groups. BISP cash transfers are one of the most cost-effective social protection measures, as they are specifically targeted towards the poorest and result in very high poverty reduction, even with a somewhat lower effect of about 1.1.

The economic and social returns in terms of PKR per unit are given in Table 8 below.

Table 8 : Economic and Social Returns per PKR

Sector	Estimated Multiplier	Poverty Impact
Infrastructure	1.4–1.6	Medium
Education	1.2–1.5	High (long-term)
Health	1.3	High
Energy subsidies	0.4–0.6	Low
BISP cash transfers	1.1	Very High

d. Agentic Scenario Simulation

The agent conducts independent fiscal scenarios and assesses the distributional and macroeconomic impact. It shows that maintaining universal energy subsidies leads to a greater fiscal gap, inflation, and a small decrease in poverty. But it would be better to get PKR 200 billion from the subsidy fund for cash transfers under BISP and PKR 100 billion from PSDP projects to mitigate the adverse impact of floods and spend a subsidy fund of PKR 300 billion on energy. The simulation reveals that re-allocative, pro-poor and climate-aware budgeting is effective because poverty can be cut by approximately 2-3 percentage points, inflation by 1-1.5% due to being more effective at targeting, and the overall fiscal stance is deficit-neutral.

e. Reinforcement Learning

The agent compares budget cycles for past years and extracts lessons that are relevant to policy, noting that the inflationary spiral and fiscal pressure of 2021-22 occurred under the use of broad subsidies, and that 2023-24, with a focus on targeted subsidies, had a "measurably better welfare outcome with less macroeconomic distortion". It highlights the benefits of increased spending in the long term and the difference that targeted spending makes, versus price controls. These insights can be utilized in subsequent budgets to improve efficiency, equity and growth.

f. Risk and Bias Management

The agent performs a multidimensional analysis of fiscal decisions by simultaneously assessing debt sustainability risks related to an increasing interest burden, identifying inequities in the region using poverty maps which indicate underfunded districts and highlight inflation risks for fiscal deficits. Built-in bias checks are being used to ensure the fairness and strength of the policy, which means that historically underfunded regions, like Balochistan and rural areas in Sindh, are not being systematically underfunded; and that gender sensitive spending is protected in critical areas such as education and health.

g. Decision Outputs

The agent automatically generates options for allocating budget based on welfare impact, fiscal sustainability and inflation sensitivity, and converts complex fiscal and macroeconomic data into actionable policy insights. It provides visualization of province-wise allocations via interactive dashboards, where policymakers can evaluate differences between the regions and make the needed decisions. The opportunity costs of different fiscal options are also made clear by poverty, inflation, and deficit trade-off charts, which help decision-makers strike a balance between macroeconomic stability and social protection.

The agentic model suggests, for example, that 0.5 percent of GDP be spent on targeted cash transfers and climate-resilient infrastructure instead of energy subsidies to maximize welfare gains, minimize fiscal burden, and boost long-term economic resilience.

7. Conclusion

In this paper, a coherent and policy-oriented view has been provided on Artificial Intelligence Architecture as a bridge between economic data and economic decisions. It shows how AI can progress economic analysis from static description to dynamic prediction, simulation, and real-time policy decisions through AI systems, having several layers such as the data layer, intelligence layer, and decision layer.

From an economic perspective, this paper has presented artificial intelligence as a helpful tool for improving economic analysis. By being able to model nonlinear dynamics, heterogeneous agents, and complex feedback mechanisms, AI is revolutionizing traditional empirical and theoretical approaches. The paper has proposed architectures for AI systems for economic analysis and applications. It highlights the role of AI in the emerging economy of Pakistan. The use cases, focused on Pakistan, show AI architecture adaptability for local needs.

The paper highlights the importance of well-developed AI architectures in the discipline of economics that connect data to intelligence and intelligence to decisions. Establishing such architectures can be a way for developing economies like Pakistan to construct more resilient, evidence-based, and inclusive economic policies. With the increasing availability of data and the complexity of the economic environment, AI architecture will become a key enabler for informed, timely, and effective economic decision making and a critical component of modern economic institutions.

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