[AUIQ Humanities and Social Sciences](https://ahss.alayen.edu.iq/journal)

Volume 2 | Issue 1 Article 1

2026

The Role of Artificial Intelligence in Macroeconomic Forecasting: A Systematic Literature Review

Thura J. Mohammed
School of Computer Sciences, Universiti Sains Malaysia, 11800 Pulau Pinang, Malaysia, thurajamal@student.usm.my

XinYing Chew
School of Computer Sciences, Universiti Sains Malaysia, 11800 Pulau Pinang, Malaysia, xinying@usm.my

Khai Wah Khaw
School of Management, Universiti Sains Malaysia, 11800 Pulau Pinang, Malaysia, khaiwah@usm.my

Recommended Citation

Mohammed, Thura J.; Chew, XinYing; and Khaw, Khai Wah (2026) "The Role of Artificial Intelligence in Macroeconomic Forecasting: A Systematic Literature Review," *AUIQ Humanities and Social Sciences*: Vol. 2: Iss. 1, Article 1.
DOI: https://doi.org/10.70176/3106-7557.1008
Available at: https://ahss.alayen.edu.iq/journal/vol2/iss1/1

AUIQ HUMANITIES AND SOCIAL SCIENCES 2 (2026) 1–15

REVIEW

The Role of Artificial Intelligence in Macroeconomic Forecasting: A Systematic Literature Review

Thura J. Mohammed [a,*], XinYing Chew [a], Khai Wah Khaw [b]

[a] School of Computer Sciences, Universiti Sains Malaysia, 11800 Pulau Pinang, Malaysia
[b] School of Management, Universiti Sains Malaysia, 11800 Pulau Pinang, Malaysia

ABSTRACT

Macroeconomic forecasting remains difficult because aggregate dynamics are nonlinear, regime-dependent, and increasingly informed by high-dimensional, mixed-frequency data, conditions under which traditional econometric models often lose accuracy, especially around turning points. This study systematically reviews how artificial intelligence (AI) is being used to address these challenges and what reliable evidence exists on its forecasting value. Using a PRISMA-aligned protocol, we searched Web of Science, Scopus, and ScienceDirect, identifying 1,627 records; after de-duplication and multi-stage screening, 178 studies were retained for qualitative synthesis. The review develops an evidence-based taxonomy of AI model families in macroeconomic forecasting and synthesizes their motivations, performance patterns, and limitations across targets such as gross domestic product (GDP) growth, inflation, and labor-market indicators. This study shows that AI methods, particularly tree-based ensembles, deep sequence models, and hybrid econometric–AI systems, frequently improve short-horizon forecasting and nowcasting in data-rich settings and during crisis regimes, but do not dominate uniformly across variables or horizons. The study's contributions are threefold: a structured taxonomy that organizes a fragmented field, a consolidated assessment of where AI gains are robust versus conditional, and a clear articulation of the main methodological and policy-relevant constraints shaping future macro-AI forecasting research.

Keywords: Artificial intelligence, Macroeconomic forecasting, GDP nowcasting, Hybrid econometric–AI models, Systematic literature review

1. Introduction

Macroeconomic predictions not only underlie key fiscal, monetary and regulatory policy decisions but also influence expectations of investors in financial markets and the real economy [1]. Aggregate variables, such as GDP growth, inflation, unemployment and output gaps, are used for example to inform stabilization strategies, risk assessments and resource allocations in both public institutions and the private sector [2]. However, it is inherently difficult to predict the future dynamics of whole economies [3, 4]. Economic become through nonlinear interactions, structural breaks, regime shifts and rare shocks that are difficult to gauge by just looking at the past [5, 6]. These problems are further exacerbated by the nature of macroeconomic data, which tend to be low frequency, relatively short in sample length, revised and suffer from measurement error; this makes it difficult to establish robust relationships [7, 8]. And in application, these restrictions curb the impact of linear-only specification and bring persistent tension between theoretical interpretablity and prediction precision

Received 5 December 2025; revised 4 January 2026; accepted 5 Jaunary 2026.
Available online 21 February 2026

* Corresponding author.
E-mail addresses: thurajamal@student.usm.my (T. J. Mohammed), xinying@usm.my (X. Chew), khaiwah@usm.my (K. W. Khaw).

https://doi.org/10.70176/3106-7557.1008

[9]. Classic stable workhorses of traditional econometric modeling such as autoregressive integrated moving-average (ARIMA) models, vector autoregression (VAR), dynamic stochastic general equilibrium (DSGE), dynamic factor and mixed-frequency models provide interpretability and theoretical discipline, but may lose predictive performance when the stability assumptions are violated and their linear structure fails [10, 11]. Meanwhile, the information set faced by forecasters has expanded massively with high-dimensional macro-financial panels, ragged-edge mixed-frequency releases and increasing reliance on Big Data [12, 13]. This convergence of richer data and more volatile environments has led to interest in AI as new types of models for predicting how much value with jurisdictional interventions add, capable of modeling nonlinearities and identifying signal amidst large, heterogeneous inputs [14, 15]. Despite the burgeoning literature, evidence in this area is scattered over model types, targets of interest, data regimes and evaluation setups [16, 17]. There is no clear consensus in empirical results, which are dispersed among studies that focus on alternative horizons, loss functions, benchmarking options and real-time data revision procedures [18]. This makes it still an open question which AI-based forecast approaches lead to systematic forecasting improvements, under what macroeconomic circumstances, and with which trade-offs compared against established econometric baselines [19, 20]. The existing surveys are often limited to a particular task or methodological thread, which leaves room for an integrative review that maps AI techniques to the full spectrum of problems encountered in macroeconomic forecasting and interprets common patterns across studies [21, 22]. To bridge this gap, this study systematically review the literature on AI in macroeconomic forecasting as per a protocol aligned to PRISMA. This corpus is applied to the development of a taxonomy of families of AI-based models in macro forecasting as well as to integrating what has been reported across studies of these model families, per their roles, empirical performance patterns and practical limitations regarding forecasting tasks and data environments. The presented study organized as follows. The basics and the fringes of conventional macroeconomic forecasting are discussed in Section 2. The methods for the systematic review are presented in Section 3. In Section 4 a taxonomy of AI model families and macroeconomic applications is given. Section 5 summarizes motivations and challenges found in the literature. Section 6 summarizes the open issues that were raised in this comparison. Section 7 concludes.

2. Macroeconomic forecasting: An overview

Macroeconomic forecast is one of the foundations and building blocks of applied economic analysis, offering predictions for aggregate quantities such as GDP growth, inflation rate, unemployment rates and interest rates [23, 24]. These forecasts underlie fiscal and monetary policy, business investment decisions, and household expectations [25, 26]. Since macroeconomic indicators represent the general status and a trend of national economies, forecasting them accurately becomes an important input for policy making and corporate sustainable development in both governmental and private sections of the economy [27]. For example, forecasting models are used by institutions such as central banks and ministries of finance as well as international organizations like the International Monetary Fund or the World Bank to forecast cyclical movements, evaluate policies' impacts on the economy, and design stabilization devices [28–30]. Historical background Macroeconomic forecasting has progressed through the history of econometric theory along with computational power [31]. Early models focused on structural and time-series approaches, based on the belief that past connections between economic variables were sufficient to predict future values [32]. Classical econometric techniques like ARIMA models, VAR or DSGE models have long been mainstays in macroeconomic forecasting [33]. Such models have interpretability and strong economic theory foundation in relationships to test policy scenarios under fixed assumptions [34, 35]. Problematically, their performance relies on linear specifications and stable data-generating processes, which conditions are often violated in practical economies featuring volatility, structural changes and regime switches [36, 37]. The shortcomings of traditional models were more and more obvious in pursuing global financial crisis, pandemics, geopolitical turbulence, worsening uncertainty and nonlinearity of the state of the macroeconomic [38, 39]. Forecasting errors commonly result from model mis-specification, omitted variables, and failure to incorporate behaviorial adjustments or feedback effects [40]. Furthermore, macroeconomic indicators are noisy by nature, subject to revisions and affected by exogenous shocks that cannot be conveniently captured in the context of standard econometric methods [41]. These difficulties have driven economists towards alternative methods while flexible enough, to capture complex, nonlinear and dynamic relationships between macroeconomic variables [42, 43]. Recent years have seen a shift towards the use of data-driven forecasting approaches using

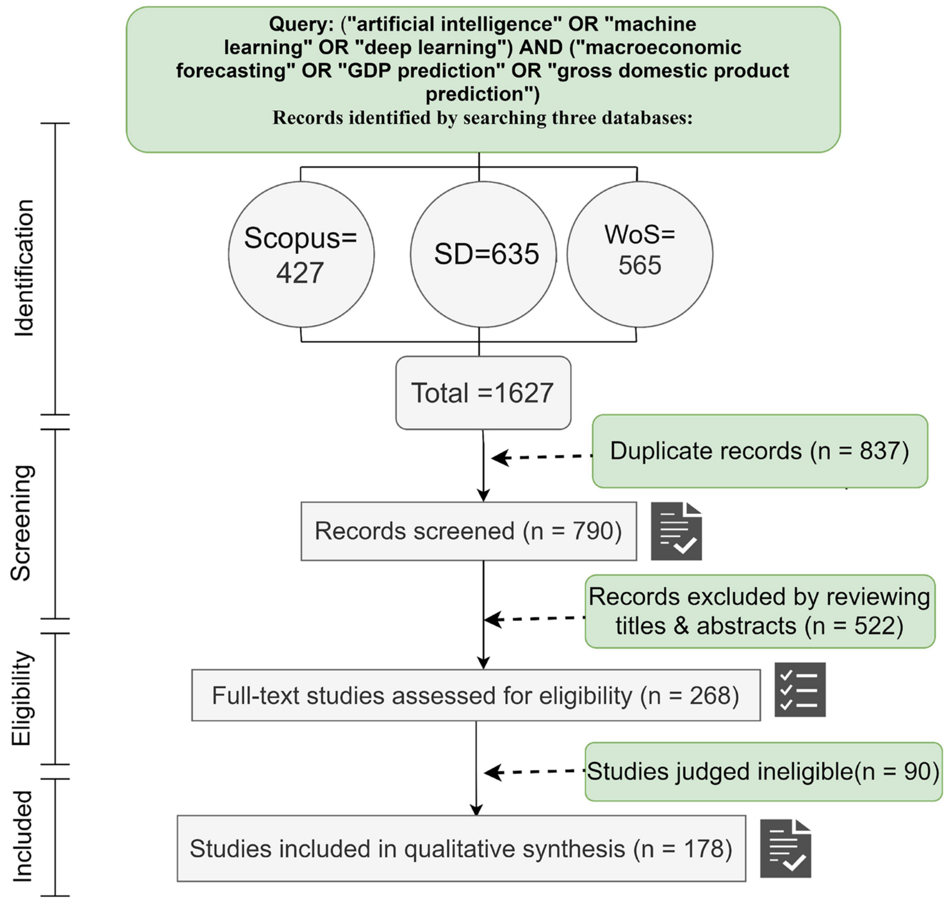

Fig. 1. SLR protocol.

computational intelligence and large-scale data integration [44]. With the exponential rise of digital data such as real-time financial transactions, sentiment and market place high-frequency time series, the empirical underpinnings on which to formulate forecast has widened [45, 46]. For this purpose, AI approaches have recently been developed and shown to give good improvements in accuracy and robustness [47, 48]. Econometric-AI models are capable of dealing with non-linearities, interactions and latent structures present in data without instituting strong parametric assumptions. Deep learning (DL) techniques have been applied to modeling complex macroeconomic dynamics and have demonstrated significant advantages over classic methods with respect to short-term and medium-term forecasting [49]. However, the embedding of AI into forecasting at macro levels also presents methodological and interpretative issues. The lack of transparency of most machine learning (ML) models obscures the economic interpretation of its results, possibly restricting adoption by policy makers familiar with transparent and theory-consistent models [50]. Moreover, the performance of AI-based predictions is particularly sensitive to data quality, feature engineering and model tuning, which demand careful design and domain knowledge [51]. But, in contrast to these concerns, the mixed approach, rapid advancement of econometric-AI pattern recognition, indicates there is significant agreement that predictive performance can move forward without giving up on theoretical grounding [52, 53].

3. Methodology

This review was designed and executed as a systematic literature review to map, evaluate, and synthesize empirical evidence on the application of AI to macroeconomic forecasting. The protocol was specified a priori and implemented in three sequential stages: structured database search, eligibility filtering via explicit criteria, and multi-stage study selection. The procedure aligns with PRISMA principles to maximize transparency and replicability, as presented in Fig. 1.

3.1. Search strategy

This review study was conducted in Web of Science, Scopus, and ScienceDirect, selected for their comprehensive coverage of economics, econometrics, and interdisciplinary AI research. Web of Science, Scopus, and ScienceDirect were selected because they offer comprehensive and high-quality coverage of peer-reviewed research in economics, econometrics, and applied AI, and are standard sources in systematic reviews in macroeconomic forecasting. Gray literature was excluded to ensure a consistent quality threshold and methodological comparability across studies. The search covered publications from 2022 to 2026, with the final search conducted in December 2025. Only English-language studies were included, reflecting the dominant publication language in the relevant literatures and ensuring consistent evaluation. As is shown in Fig. 1, a Boolean search query was created aiming to retrieve studies with the use of AI methods for macroeconomic forecasting by mixing AI-related keywords and macroeconomic forecasting terms. The last search string was ("artificial intelligence" OR "machine learning" OR "deep learning") AND ("macroeconomic forecasting" OR "GDP" OR "gross domestic product"). Minor syntactic revisions to the query were performed in order to adapt it for the particular database syntax while keeping its logic unchanged. The searches were not constrained with regard to geographic scope in order to be able to include cross national evidence, and the search was restricted to academic records indexed in databases. After removing the duplicates, 565, 427 and 635 records in Web of Science, Scopus and ScienceDirect were obtained respectively, contributing to a total of 1627 studies in the searching phase.

3.2. Eligibility criteria

Inclusion criteria were prespecified to ensure that included studies focused squarely on AI-generated forecasts of macroeconomic aggregates. Studies were considered for inclusion only if they employed AI, machine learning (ML) or deep learning (DL) as a main forecasting technique; focused on macro-level aggregate economic variables including GDP level or growth, inflation, unemployment rate, industrial production, output gap, business-cycle indicators and macro-risk measures; and contained a numeric out-of-sample forecasting exercise with quantitative performance assessment using real-world macroeconomic data. Only peer-reviewed articles, indexed conference studies and high-quality working studies were included. Ineligible studies were those with micro-level or financial but no macro target outcome, that forecasted only based on traditional econometric models without AI element, that did not present quantifiable forecasting evaluation and in which method processes are too opaque to determine validity.

3.3. Study selection

The selection of studies was followed in three stages. Initially, the combined records were deduplicated bedding down 837 duplicates and resulting in a total of 790 studies. Second, the titles and abstracts of these 790 records were screened for eligibility criteria, leading to exclusion of 522 studies at this phase that did not forecast macroeconomic aggregates, did not use AI approaches for forecasting or have an evaluation forecasting design as part of it; thus, completing with a pool of 268 studies to be assessed in detail. At both the screening and full-text assessment stages, any disagreements were resolved through discussion until consensus was achieved. Third, the full articles of the 268 studies that remained were examined to ensure methodological appropriateness and conformity to inclusion criteria. 90 studies at this stage were excluded, mostly owing to (i) lack of out-of-sample evaluation, (ii) non-macroeconomic targets or (iii) peripheral and not yet a substantive use of AI for forecasting. The resultant corpus is 178 studies and would be used in the qualitative synthesis.

4. AI models in in macroeconomic forecasting: Taxonomy

Studies were assigned to AI model families based on their dominant forecasting architecture and the functional role of AI within the modeling framework. Classification was guided by whether AI methods operated as standalone forecasters, sequence learners, residual or weight learners within econometric structures, decomposition-based predictors, or probabilistic density estimators. When studies employed multiple techniques, classification reflected the component driving the primary forecasting contribution. Of the 178 studies included after the full-text screening, this study finds that AI in macroeconomic forecasting is not a monolithic methodological line but rather a heterogeneous ensemble of model families tailored to fulfill disparate forecasting roles in face of macro data constraints. Macro series tend not only to be short and low-frequency, but also are revised over time and subject to regime shifts, so researchers have developed AI through a variety of structurally different lenses instead of homing in on a single dominant algorithm. This necessitates a sort of taxonomy that coordinates this evidence base; that tidies up how model choice relates to forecasting tasks (GDP, inflation, unemployment, output gaps,

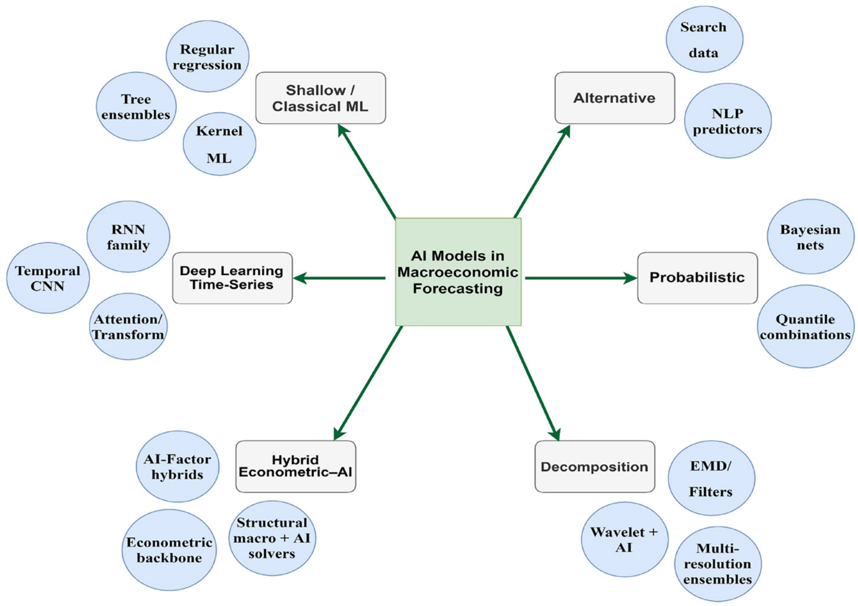

Fig. 2. Taxonomy of AI models in macroeconomic forecasting.

recession risks); and for synthesizing comparative performance in due course as in Fig. 2.

4.1. Shallow/Classical ML forecasters

The classical ML forecasters frame macroeconomic prediction as a supervised regression and treat temporal dependence through lags, rolling windows or factor summaries but not learned end to end [54, 55]. This family contains penalized linear learners (ridge, LASSO, elastic net and extensions), tree-based ensembles (random forests, gradient boosting, XGBoost, quantile forests) and kernel methods such as support-vector regression [56, 57]. Penalized linear models and tree-based ensembles are grouped within the same "shallow/classical ML" family because they share a common modeling paradigm: temporal dependence is introduced through explicit feature engineering (lags, rolling windows, or factor summaries), and model complexity is limited relative to deep architectures. The linear mixed model approach has a strong application track record in GDP growth, inflation, unemployment forecasting and wide horse-race benchmark studies for data-rich macro panels or mixed predictor environments [58, 59]. It's not a coincidence that their strengths are practical; they readjust well to high-dimensional predictors, achieve robust out-of-sample gains over linear baselines, and allow for relatively interpretable diagnostics via sparsity patterns or feature importance [60, 61]. The nature of their architecture leads to their limitations: as dynamics are imposed by feature engineering, they have difficulty capturing long-memory nonlinearities or regime-dependent patterns without a great deal of manual design, and results are dependent upon lag selection, targeting, and screening rules [62, 63].

4.2. DL for macroeconomic time series

In time series-DL models, the forecasting engine learns temporal dependence from sequences. The dominant sub-stream depends on recurrent models, particularly LSTM and GRU nets; some studies use the reservoir/echo-state or temporal convolutional networks, N-BEATS-style multi-horizon systems and more and more attention-based or transformer kin largely engineered for macro panels [64, 65]. These are particularly widespread in GDP nowcasting/forecasting, inflation forecasting during instability, and business-cycle state prediction, especially when information sets are large, mixed-frequency or incorporate real-time indicators [66, 67]. Their primary benefit comes from representation learning: deep architectures decrease dependence on handcrafted lags and may internalize non-linear state evolution between horizons/predictors. But macro settings also reveal fragilities of DL [68, 69]. Short sample length results in overfitting, predictive benefits are episodic and crisis-specific, and performance depends on the training protocol, indoor data processing method and evaluation criterion. Consequently, deep models are more likely to show the greatest improvements for nowcasting information-rich, short-horizon tasks, and their advantage may be less certain at longer horizons.

4.3. Hybrid econometric–AI systems

Another family is characterized by hybrid systems where AI is grafted onto an econometric trunk instead of replacing it [70, 71]. Such studies hybridize macro structures (classical or dynamic factor models, MIDAS or bridging equations, VAR/BVAR systems), basic ML filters to learn nonlinear residuals, regime dependent adjustments, component forecasts or state varying combination weights with MLs. Hybrids are particularly prevalent in policy-related forecasting where interpretability, stability, and institutional longevity count for something [72, 73]. These are common use cases for mixed-frequency GDP nowcasting, inflation forecasting with ML corrections to structural baselines, and multivariate macro forecasting with AI-augmented VARs. The robustness of this family lies in the complementarity of approaches: econometric structure lends coherence and justifiable economic interpretation; AI offers nonlinear flexibility and high-dimensional adaptation [54, 55]. The limitation here is the conditionality: when the backbone model has already captured a large fraction of predictive content, AI contributes only weakly; and in case of loosely specified backbones, hybrids may inherit structural biases [74, 75]. Forecast gains are then conditioned on the econometric core and AI layer both being well-constructed in conjunction.

4.4. Decomposition and multi-scale AI forecasting

Across the reviewed studies, decomposition parameters are typically chosen using standard conventions or data-driven rules, such as commonly used frequency cutoffs in filtering approaches or empirical mode counts selected based on variance or energy criteria. Several studies report sensitivity analyses that evaluate forecasting performance under alternative decomposition settings, generally finding that gains are robust within reasonable parameter ranges, though performance can deteriorate under aggressive or poorly tuned decompositions. In decomposition-based systems, the defining step is to separate macro series (and often predictors) into components, trend and cycle, frequency bands, or intrinsic modes, before applying AI to forecast each part and recombining them. Wavelet-neural hybrids, EMD/VMD-plus-ML pipelines, and filter-then-deep models are emblematic designs [76, 77]. This family is widely used in applications to inflation and GDP forecasting, scenarios characterized by non-stationarity, multi-frequency dynamics and noise which may confuse monolithic learners [78, 79]. Its key benefit lies in its stability: disconnecting the low-frequency cycles from high-frequency shocks enables cleaner learning targets, commonly leading to robust short-horizon gains and stronger performance around turning points [80, 81]. Its disadvantage is increased reliance on the choice of decomposition [82, 83]. Gains can depend on filter parameters, mode counts or frequency cutoffs, making the process of porting to other countries and data vintages less straightforward unless appropriately validated [84, 85].

4.5. Probabilistic/Bayesian AI and density forecasting

This category focus on predictive distributions, tail risks, and uncertainty-aware macro forecasting rather than point forecasts. These include Bayesian neural networks with shrinkage priors, stochastic-volatility-augmented deep models, variational Bayes for scaling large BVARs, quantile-focused tree ensembles and Bayesian ML [86, 87] to learn nonlinear density-combination weights across forecasters. This included density forecasts of GDP growth and inflation, estimation of the probability of recession, downside-risk and macro-stress measures, and forecast-combination for surveys or institutional projections. The benefit of the presented category lies in decision relevance: the predictive distributions describe asymmetry and regime-dependent uncertainty that are important for policy and risk management [88, 89]. Limitations remain nontrivial. Bayesian training can be computationally intensive, evaluation modes are diverse (log scores, CRPS, calibration), and evidence for density forecasting continues to be more limited in variable coverage and spatial extend than for point prediction [90, 91].

4.6. AI with alternative and unstructured data

In this category, AI is applied mostly for transforming alternative or unstructured data into predictive signals. These works extract predictors from central-bank narratives, news or reports through NLP pipelines (from dictionary/elastic-net lexicons to transformer embeddings), or digital traces such as search intensity and similar high-frequency proxies [60, 92]. The main novelty is the extension of information to beyond conventional macro indicators which in practice tends to result in better short-horizon GDP and inflation nowcasts while it can help rationalize forecast errors during crises. The power here is informational promptness: text and digital indicators often lead official data and encode expectations, sentiment and uncertainty [93, 94]. The limitation is that it is fragile to context drift and measurement noise; the predictive content may be episodic, domain-specific, and sensitive to corpus definition, thus setting a high bar for strict real-time out-of-sample validation [95, 96]. A

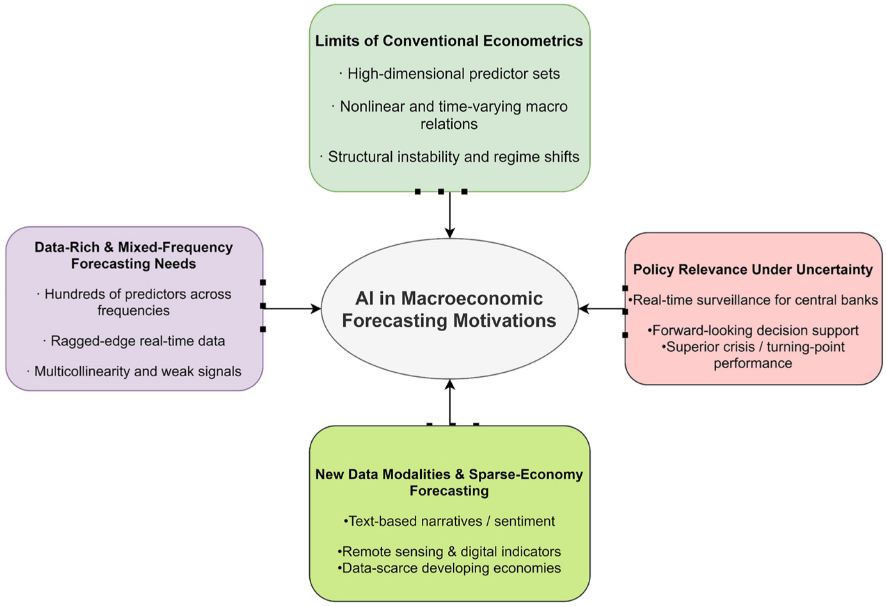

Fig. 3. Motivations for applying AI in macroeconomic forecasting.

number of systematic trends are apparent across model families [97]. Fourth, the literature has transitioned from overreliance on shallow ML to much more rapid growth in deep sequence models post late-2010s with richer data and better training practice facilitating developments, although gains are still mixed for variables-by-horizons [98–100]. And second, econometric-AI hybrids are becoming more powerful in policy-relevant work, because institutions prefer AI-augmented rather than AI-displacing economic cores [101]. Third, probabilistic and density-forecasting applications are increasing, suggesting a shift away from the mode of accuracy competitions toward more risk-conscious macroeconomic forecasting, but less common than point-forecast studies[93], [102]. Finally, the adoption of new sources of unstructured data, especially text-based sentiment and digital traces has become an important frontier, thus hinting that future forecasting progress may come as much from richer information sets than novel architectures [103, 104]. Such a taxonomy lays the ground for the ensuing discussion, which analyses performance profiles by macro targets, data regimes and forecasting horizons[105, 106].

5. Discussion

5.1. Motivations

Across the reviewed corpus, the shift toward AI-driven macroeconomic forecasting is motivated by a shared diagnosis: conventional econometric frameworks struggle in environments that are simultaneously high-dimensional, nonlinear, and structurally unstable, as presented in Fig. 3. Many studies emphasize that modern macro datasets now contain hundreds of candidate predictors at multiple frequencies, making classical linear or tightly parameterized models prone to overfitting or to discarding useful signals through restrictive structure [107, 108]. AI methods, regularized regressions, tree ensembles, and deep networks, are adopted precisely because they can compress large information sets, tolerate multicollinearity, and learn complex interactions without imposing a priori linearity [109, 110]. This motivation is explicit in work comparing ML algorithms with “gold standard” factor models for GDP forecasting, where ML models are framed as a way to uncover nonlinear and time-varying relationships that traditional tools may miss, especially under rapid economic change [111, 112]. A second, quite frequently recurring motivation is policy relevance with uncertainty. AI models are often framed as instruments to bolster real-time surveillance and forward-looking policy decisions on the part of central banks and fiscal authorities [113, 114]. Evidence from GDP forecasting in China implies that ML models lead to much lower out-of-sample errors and are more successful during the COVID period, suggesting their potential advantage when regimes change suddenly [115, 116]. By the same measure, those who study fiscal risk say AI provides “empirical flexibility,” even as it may be rooted in theory, to establish early warning systems that would allow policymakers to see where stress signals are falling and thus prevent linear models from missing them. Third, the fast growth of the literature mirrors the emerging omics and measurement requirements. Some articles include in forecasting pipelines text-as-data, remote sensing or domain-specific big data motivated by the idea that narratives and other indicators can capture sooner than standard releases latent expectations and shocks. For instance, the sentiment from Brazilian central bank minutes enhances GDP now-casting accuracy, and it is able to explain market forecast errors suggesting that AI-driven textual features include incremental information beyond numeric series [117]. At the same time, for emerging markets and data-sparse AI is motivated as a practical alternative to generating usable forecasts despite small samples; adversarial or transfer-learning based methods are used to optimize learning in small datasets.

5.2. Challenges

Although including performance increases, the studies also agree on a number of methodological and practical challenges. A prevailing challenge is data quality and real-time assurance. A large number of applications of AI are based on low (perhaps revised) frequency time series and this can cause a loss in responsiveness and artificially inflated apparent accuracy [117, 118]. At a practical level, fiscal-stress modeling acknowledges that the use of annual data may inhibit timely identification and advocates supplementing compiled higher-frequency fiscal and market indicators to facilitate real-time application. Relatedly, missing, mixed frequency, revisions are and will continue to be issues in macro forecasting; AI can handle it, but results depend on pre-processesing/feature choice. A second issue is interpretability and institutional confidence [119, 120]. The literature again and again refers to complex AI models as “black boxes” which, in policy-making settings where causal narratives, transparency and accountability matter, hampers the adoption of these techniques [121, 122]. Even if precision is better, policy institutions remain skeptical when the model’s levers can’t be described in economically coherent ways. As such, work underscores interpretability as a constraint and recommends methods such as SHAP or variable-importance analysis to recover economically meaningful signals. Third, there is the problem of model instability across regimes. Some articles demonstrate that the relative standings of models shift in tranquil times and crises suggesting there is no one size fits all AI architecture which is best. China GDP evidence suggests that DA shrinkage with ridge type has a particularly good performance in the uncertain case, while RD forest leads to robust gains under stability, hence ML success vary by shock environment [123]. This sensitivity to regime is intimately tied to risks of overfitting and temporal leakage; upon revealing macro-orderings in time, naive out-of-time cross validation dies, even for powerful models we observe mild decay as the model learns whilst being temporally validated. Last, generalization and scope treatment is uneven [124, 125]. Some of the DL-GDP works are context-depending (for example, urban profiling or single-country cases), which makes the portability between economies with different structures and data coverage or institutions debatable [126]. Additionally, the field does not have standard benchmarks for density forecasting, turning-point prediction or multi-horizon evaluation which hampers cumulative progress [127, 128].

5.3. Recommendations

The corpus developed backs a series of future-facing technical and institutional recommendations. First, future research must proceed with hybrid macro-AI systems that integrate theoretical discipline and ML flexibility [129]. Studies to this literature indicate that in principle ML would be implemented through inclusion of the technique in structured frameworks (e.g., inter-temporal budget constraints or reaction functions) that are explicitly designed to link predictive gains with economically interpretable policy signals [130]. In the line of GDP forecasting, some studies also present ML as a complement rather than alternative to factor models, proposing forecast combinations that exploit both structural and data-driven advantages. Second, integrating real-time and high-frequency data is a priority for researchers. The aforementioned repeated worry on a low-frequency dependence suggest that next-generation models may need to gradually include monthly/weekly fiscal and financial indicators, online activity metrics or other big-data streams as input for nowcasting and early warning. A closely related one is the suggestion for dynamic updating (for example, rolling or online learning) so that models can adjusts to changing regimes rather than being originally trained on only a fixe historical window. Third, the literature promotes a systematic embrace of XAI as the norm rather than a supplement. Being one-shot its (for an installed model) from prediction to policy narrative and AI outputs actionable in central-bank and ministry workflows, interpretability layers SHAP, partial dependence, Shapley-based decomposition, and economically informed feature grouping are advised [131, 132]. Fourth, there is a clear methodological call for macro-appropriate evaluation standards. Studies recommend time-series-aware cross-validation, multi-horizon pseudo-out-of-sample testing, and greater attention to distributional accuracy (density forecasts, tail risks) rather than only point RMSE [133]. Finally, for data-constrained settings, promising directions include transfer learning and adversarial training to improve robustness when samples are small, an approach already showing strong gains in developing-economy GDP forecasting.

6. Gaps, open issues, and innovative key solutions

The 178 core studies synthesized in this review demonstrate meaningful progress in applying AI to macroeconomic forecasting, yet they also reveal persistent limitations that prevent the literature from converging on stable best practices. The gaps are not only technical (model choice) but structural (data, evaluation, and institutional use). This section consolidates those open issues and outlines solution pathways that emerge directly from the evidence base.

6.1. Evidence fragmentation and lack of cumulative benchmarking

One of the key lacunas is the disjointedness of evidence. Many studies provide single-country or single-variable applications with idiosyncratic sets of predictors, training windows and benchmarking [76]. Even when improvements are shown, they can hardly be compared between studies due to differing baseline models, different vintages of data and different horizons at which the method was tested [54, 134]. Such horse-race studies can reveal a high dependency on test data properties, but few have replicated their results on shared benchmark panels or made their pipelines portable. As a result, the field could end up with isolated "success stories" rather than cumulated understanding of when AI wins and doesn't. The literature claims a lack of standard macro-AI benchmark suites similar with computer vision or NLP [43]. These might need to be common benchmarks, such as common goals and rolling fixed evaluation protocols [1]. A complementary answer is open, versioned forecasting pipelines that allow one to reproduce the results under uniform hyperparameter and data-revision rules, for "meta-comparisons" across countries and horizons [14].

6.2. Real-time validity and data revision risk

A second unsolved problem is that the majority of works do not work under real-time situations. A lot of the AI predictions are trained on smooth macro series, which gives ersatz precision and masks operational error. Moving away from AI at turning points pays off, turning points are when revisions tend to be largest and ragged-edge data problems are worst. Mixed-frequency deep models and Google Trends/text-based indicators can assist; however, the corpus still treats the real-time data discipline as an exception rather than a standard [5, 13]. Analyses suggest two potential roads forward: (i) training the model as default on real-time vintages in conjunction with an explicit accounting of revision sensitivity, and (ii) "measurement-augmented forecasting," whereby replacement high-frequency indicators (e.g., text, search intensity, mobility, energy traces, etc.) are not treated as ad hoc addendums to nowcasting systems but rather become structured parts thereof. Real-time conformal prediction, which is already seen working in studies that focus on density-based measures (including this one), offers a scalable means to produce uncertainty intervals with validity under revision noise [55, 91].

6.3. Small-sample DL and overfitting

While DL has exploded, the small-T macro environment is still a binding constraint. However, several studies that exhibit outperformance over benchmarks by deep models focus mostly on short-horizon nowcasting or crisis windows and lose their edge when data become sparse or the horizon is lengthened [46, 135]. Bayesian neural networks and shrinkage offer promise but are currently less popular. That is, the community hasn't quite figured out how to roll-out good high-stakes-level learners in a macro-sample constrained manner. The corpus of results points to three recipes for solutions: (i) Bayesian DL with macro-specific priors (horseshoe, activation mixtures, stochastic volatility layers) to regulate capacity; (ii) De-composition-first architectures that would remove noise and increase the effective sample signal; and (iii) transfer-learning schemes between countries or related macro targets, especially for other developing economies where available data are dominated by shallow annual datasets [50, 136]. These methods consider data sparsity not as a hindrance, but rather as an issue to be factored into the design process.

6.4. Regime instability and nonstationarity

A consistent gap is the limited treatment of regime change. Many studies acknowledge that AI gains are state-dependent, yet only a subset explicitly models recession/expansion regimes, structural breaks, or crisis-driven parameter drift. So even if some forecasters are correct during the calm, others could be dead wrong when policy interest is peaked [44, 95]. Regime uncertainly also discourages out-of-sample generalization and adds complication for model selection. Solutions found in the literature include: understanding regime attention; rolling/online updating; and mixed solutions where econometric structure provides long-run anchor while AI captures non-linear deviations [3]. One promising frontier is conditional forecasting systems: models that condition explicitly on measures of uncertainty, financial stress, or business-cycle regimes to adjust their functional form when they forecast rather than only once the fact that they made errors becomes apparent [19].

6.5. Limited density forecasting and Tail-risk coverage

A major open issue is that most AI macro articles still prioritize point forecasts. Density forecasting, downside-risk estimation, and state-dependent forecast combination are growing strands, but they remain narrow in variable scope and geographic application. Yet policy decisions often hinge on tail outcomes, not means [1, 19]. Without broader density evidence, AI's institutional value remains underexploited. The evidence supports scaling probabilistic ML methods, Bayesian neural nets, quantile forests, variational Bayes BVARs, and nonlinear density-combination learners, into standard macro forecasting practice [13, 55, 91]. Another solution is hybrid probabilistic systems: using AI to learn nonlinear forecast weights while classical models contribute coherent structural distributions. This would integrate risk-based macro monitoring with the predictive advantages of AI [3, 50].

6.6. Interpretability and policy integration gaps

Even where AI increases accuracy, its institutional adoption is limited by the need for interpretability [34, 83]. Studies insist again and again that black-box gains don't get central banks or fiscal authorities there, they require defensible narratives about drivers, uncertainty and structural coherence. SHAP and other feature-importance tools are starting to materialize, however interpretability is still an afterthought more than a first-class design goal [4, 57]. The literature also suggests a pivot toward "native interpretability," that is, explanation encoded as part of model structure. Examples include deep models that decompose and then reconcile themselves naturally with "trend/cycle" type narratives, hybrid models where AI learns the residuals around understandable baselines, or probabilistic outputs which map to risk-communication frameworks. Relatedly, provision also appears useful for economically 'bundling' feature attributions (e.g., demand vs supply blocks, domestic vs external shocks), so that AI explanations can align closely with the language of macro policy discussions [35, 137].

7. Conclusion

This systematic literature review synthesized 178 studies on the role of AI in macroeconomic forecasting. The evidence shows that AI has moved from a niche alternative to a substantive forecasting toolkit, particularly in data-rich and mixed-frequency environments and in periods of heightened uncertainty. Across the literature, gains are most consistently associated with tree-based ensembles, deep sequence models, and hybrid econometric–AI systems, while probabilistic and text-augmented approaches are emerging as important frontiers for policy-relevant forecasting. At the same time, the review highlights that AI does not deliver uniform superiority over traditional econometric baselines. Performance advantages are contingent on data quality, horizon, regime stability, and disciplined evaluation. Persistent challenges, small effective samples, structural breaks, reproducibility gaps, and interpretability barriers, continue to limit fully reliable and institutionalized adoption. Overall, AI should be viewed less as a replacement for macro econometric structure and more as a complementary set of methods whose value depends on careful integration with macroeconomic data realities and policy requirements. Future progress in the field will rely on cumulative benchmarking, real-time validation, and forecasting systems that balance predictive strength with transparency and robustness.

Conflict of interest

The authors declare no conflict of interest.

Author contribution

All authors contributed equally to the conceptualization, methodology, data analysis, writing, and revision of the manuscript.

Data availability

No datasets were generated or analyzed during the current study.

References

1. Chernis T, Hauzenberger N, Huber F, Koop G, Mitchell J. Predictive Density Combination Using Bayesian Machine Learning. Int Econ Rev (Philadelphia). 2025;66(3):1287–1315. doi: 10.1111/iere.12759.

2. Mutai NC, Farag K, Ibeh L, Chelabi K, Nguyen NM, Popoola OM. AI Driven Fiscal Risk Assessment in the Eurozone: A Machine Learning Approach to Public Debt Vulnerability. FinTech. 2025;4(3). doi: 10.3390/fintech4030027.
3. Pitta de Jesus DP and da Nobrega Besarria C. Central Bank Narratives and Macroeconomic Forecasting: Using Textual Analysis from Machine Learning. IMF Economic Review. 2025. doi: 10.1057/s41308-025-00278-x.
4. Saadouni S, Ammari S, Habbani S. Unveiling Global Economic Stratification: A Machine Learning Framework for Multi-Dimensional Macroeconomic Analysis. Data and Metadata. 2025;4. doi: 10.56294/dm20251180.
5. Goulet Coulombe P, Leroux M, Stevanović D, Surprenant S. How is machine learning useful for macroeconomic forecasting?. Journal of Applied Econometrics. 2022;37(5):920–964. doi: 10.1002/jae.2910.
6. Šilhavy P, Hlaváčková-Schindler K, Silhavy R. Minimum Description Length and Multi-Criteria Decision Analysis in Predictive Modeling. IEEE Access. 2025;13:19388–19407. doi: 10.1109/ACCESS.2025.3532815.
7. Lin W, Wei Y. Economic forecasting with big data: A literature review. Journal of Management Science and Engineering. 2024;9(2):254–270. doi: https://doi.org/10.1016/j.jmse.2024.01.003.
8. Ellingsen J, Larsen VH, Thorsrud LA. News media versus FRED-MD for macroeconomic forecasting. Journal of Applied Econometrics. 2022;37(1):63–81. doi: 10.1002/jae.2859.
9. Huang D, Jiang F, Li K, Tong G, Zhou G. Scaled PCA: A New Approach to Dimension Reduction. Manage Sci. 2022;68(3):1678–1695. doi: 10.1287/mnsc.2021.4020.
10. Adeyemo AC, Bogdandy B, Toth Z. and IEEE, Machine Learning based Prediction of GDP using FAO Agricultural Data Set for Hungary, 2021. doi: 10.1109/SACI51354.2021.9465608.
11. Jallow H, Gibba A, Mwangi RW, Imboga H. GDP prediction of The Gambia using generative adversarial networks. Front Artif Intell. 2025;8. doi: 10.3389/frai.2025.1546398.
12. Kumar S, Shukla AK, Muhuri PK, Lohani QMD. CO2 emission based GDP prediction using intuitionistic fuzzy transfer learning. Ecol Inform. 2023;77. doi: 10.1016/j.ecoinf.2023.102206.
13. Coulombe PG, Leroux M, Stevanovic D, Surprenant S. How is machine learning useful for macroeconomic forecasting?. Journal of Applied Econometrics. 2022;37(5):920–964. doi: 10.1002/jae.2910.
14. Ballarin GZ-. Essays in Time Series Econometrics and Machine Learning. 2024.
15. Alaminos D, Salas MB, Fernandez-Gamez MA. Quantum Computing and Deep Learning Methods for GDP Growth Forecasting. Comput Econ. 2022;59(2):803–829. doi: 10.1007/s10614-021-10110-z.
16. Chen S, Han X, Shen Y, Ye C. Application of Improved LSTM Algorithm in Macroeconomic Forecasting (Retracted Article). Comput Intell Neurosci. ;2021;2021. doi: 10.1155/2021/4471044.
17. Liu YZ-. Essays on Methods for Forecasting Using High Dimension Data. 2024.
18. Liu T and Cheng H. CAN THE CLASSICAL ECONOMIC MODEL IMPROVE THE PERFORMANCE OF DEEP LEARNING? A GDP FORECASTING EXAMPLE. ROMANIAN JOURNAL OF ECONOMIC FORECASTING. 2024;27(2):86–110.
19. Gareev MY and Polbin V A. Nowcasting Russia's key macroeconomic variables using machine learning. Vopr Ekon. 2022;(8):133–157. doi: 10.32609/0042-8736-2022-8-133-157.
20. Li Q, Yu C, Yan G. A New Multipredictor Ensemble Decision Framework Based on Deep Reinforcement Learning for Regional GDP Prediction. IEEE ACCESS. 2022;10:45266–45279. doi: 10.1109/ACCESS.2022.3170905.
21. Cheng M. Harnessing volatility cascades with ensemble learning. J Forecast. 2024;43(8):2954–2981. doi: 10.1002/for.3166.
22. Kumar S, Muhuri PK. A novel GDP prediction technique based on transfer learning using CO2 emission dataset. Appl Energy. 2019;253. doi: 10.1016/j.apenergy.2019.113476.
23. Maehashi K, Shintani M. Macroeconomic forecasting using factor models and machine learning: an application to Japan. J Jpn Int Econ. 2020;58. doi: 10.1016/j.jjie.2020.101104.
24. Liu E, Zhu H, Liu Q, Udimal TB. Regional Economic Forecasting Method Based on Recurrent Neural Network. Math Probl Eng. 2022:2022. doi: 10.1155/2022/3058947.
25. Longo L, Riccaboni M, Rungi A. A neural network ensemble approach for GDP forecasting. J Econ Dyn Control. 2022;134. doi: 10.1016/j.jedc.2021.104278.
26. Michalak K, Raciborski R. Dynamic correlation approach to early stopping in artificial neural network training. Macroeconomic forecasting example, 2005. doi: 10.1109/ISDA.2005.41.
27. Ortega-Bastida J, Gallego AJ, Rico-Juan JR, Albarran P. A multimodal approach for regional GDP prediction using social media activity and historical information. Appl Soft Comput. 2021;111. doi: 10.1016/j.asoc.2021.107693.
28. Pang C. Construction and Analysis of Macroeconomic Forecasting Model Based on Biclustering Algorithm. Journal of Mathematics. 2022:2022. doi: 10.1155/2022/7768949.
29. Lai H. A comparative study of different neural networks in predicting gross domestic product. Journal of Intelligent Systems. 2022;31(1):601–610. doi: 10.1515/jisys-2022-0042.
30. Molwantoa LZ-. South African Inflation Forecasting Using Genetically Optimised Neural Networks. 2013.
31. Syed AAS, Lee KH. Macroeconomic forecasting for Pakistan in a data-rich environment. Appl Econ. 2021;53(9):1077–1091. doi: 10.1080/00036846.2020.1826399.
32. Wang T, Du Y, Cui Z. Research on Macroeconomic Prediction Technology Based on Wavelet Neural Network, 2022. doi: 10.1007/978-981-16-9735-7_9.
33. Coulombe PG, Leroux M, Stevanovic D, Surprenant S. Macroeconomic data transformations matter. Int J Forecast. 2021;37(4):1338–1354. doi: 10.1016/j.ijforecast.2021.05.005.
34. Araujo GS, Gaglianone WP. Machine learning methods for inflation forecasting in Brazil: New contenders versus classical models. Latin American Journal of Central Banking. 2023;4(2). doi: 10.1016/j.latcb.2023.100087.
35. Duan Y, Goodell JW, Li H, Li X. Assessing machine learning for forecasting economic risk: Evidence from an expanded Chinese financial information set. Financ Res Lett. 2022;46. doi: 10.1016/j.frl.2021.102273.
36. Kumar S, Shukla AK, Muhuri PK, Lohani QMD. and IEEE, Transfer Learning based GDP Prediction from Uncertain Carbon Emission Data, 2019. doi: 10.1109/FUZZ-IEEE.2019.8858917.
37. Zhang Y, Shang W, Zhang N, Pan X, Huang B. Quarterly GDP forecast based on coupled economic and energy feature WA-LSTM model. Front Energy Res. 2023;11. doi: 10.3389/fenrg.2023.1329376.
38. Li Q, Yan G, Yu C. A Novel Multi-Factor Three-Step Feature Selection and Deep Learning Framework for Regional GDP Prediction: Evidence from China. Sustainability. 2022;14(8). doi: 10.3390/su14084408.

39. Phage KZ-. Forecasting South Africa's Inflation Rate Using Deep Neural Networks. 2022.
40. Xu X, Rogers RA, Estrada MAR. A Novel Prediction Model: ELM-ABC for Annual GDP in the Case of SCO Countries. Comput Econ. 2023;62(4):1545–1566. doi: 10.1007/s10614-022-10311-0.
41. Kumar S and Muhuri PK. A concise review towards a novel target specific multi-source unsupervised transfer learning technique for GDP estimation using CO2 emission data. Artif Intell Rev. 2024;57(12). doi: 10.1007/s10462-024-10858-4.
42. Silhavy P, Hlavackova-Schindler K, Silhavy R. Minimum Description Length and Multi-Criteria Decision Analysis in Predictive Modeling. IEEE Access. 2025;13:19388–19407. doi: 10.1109/ACCESS.2025.3532815.
43. Smirnov VS. Machine learning methods in macroeconomic forecasting: Preliminary results. Vopr Ekon. 2025;(10):131–154. doi: 10.32609/0042-8736-2025-10-131-154.
44. de Jesus DP, da Nobrega Besarria C. Central Bank Narratives and Macroeconomic Forecasting: Using Textual Analysis from Machine Learning. IMF Economic Review. 2025. doi: 10.1057/s41308-025-00278-x.
45. Yoon J. Forecasting of Real GDP Growth Using Machine Learning Models: Gradient Boosting and Random Forest Approach. Comput Econ. 2021;57(1):247–265. doi: 10.1007/s10614-020-10054-w.
46. Rebelo MACZ-. Interpretabilidade de Modelos Machine Learning para a Previsão Macroeconómica. 2022.
47. Ballarin G, Dellaportas P, Grigoryeva L, Hirt M, van Huellen S, Ortega J-P. Reservoir computing for macroeconomic forecasting with mixed-frequency data. Int J Forecast. 2024;40(3):1206–1237. doi: 10.1016/j.ijforecast.2023.10.009.
48. Fang P, Gao Z, Tsay RS. Supervised kernel principal component analysis for forecasting. Financ Res Lett. 2023;58. doi: 10.1016/j.frl.2023.104292.
49. Xiao H, Li X, Yang J, Ye X. Can AI-Driven National ESG in Big Data Help Improve Macroeconomic Forecasting?. Romanian Journal of Economic Forecasting. 2025;29(2):84–103.
50. Osman BM and Muse AMS. Predictive analysis of Somalia's economic indicators using advanced machine learning models. Cogent Economics & Finance. 2024;12(1). doi: 10.1080/23322039.2024.2426535.
51. Ngoc LDT, Hoan ND, Nguyen H-N. Gross Domestic Product Forecasting Using Deep Learning Models with a Phase-Adaptive Attention Mechanism. Electronics (Basel). 2025;14(11). doi: 10.3390/electronics14112132.
52. Yu Y. GDP Economic Forecasting Model Based on Improved RBF Neural Network. Math Probl Eng. 2022;2022. doi: 10.1155/2022/7630268.
53. Seregina EZ-. Graphical Models in Financial Econometrics and Macroeconomic Forecasting. 2021.
54. Celik SSZ-. Predicting External Macroeconomic Crises: Machine Learning Perspective. 2024.
55. Hopp D. Benchmarking econometric and machine learning methodologies in nowcasting GDP. Empir Econ. , 2024;66(5):2191–2247. doi: 10.1007/s00181-023-02515-6.
56. Kuang Y, Singh R, Singh S, Singh P. A novel macroeconomic forecasting model based on revised multimedia assisted BP neural network model and ant Colony algorithm. Multimed Tools Appl. 2017;76(18):18749–18770. doi: 10.1007/s11042-016-4319-9.
57. Zhang Q and Bian Y. Understanding Machine Learning-based Methods in Macroeconomic Forecasting: Tracking Chinese GDP Growth Rate. Comput Econ. 2025. doi: 10.1007/s10614-025-11115-8.
58. Wang Y, Ghazali MF, Razak RAb, Zaidi MAS. Complex system and PS-LSTM prediction of cryptocurrencies, stocks, bonds, exchange rates and commodities. Physica A: Statistical Mechanics and its Applications. 2025;679:130976. doi: https://doi.org/10.1016/j.physa.2025.130976.
59. Diebold FX, Göbel M, Goulet Coulombe P. Assessing and comparing fixed-target forecasts of Arctic sea ice: Glide charts for feature-engineered linear regression and machine learning models. Energy Econ. 2023;124:106833. doi: https://doi.org/10.1016/j.eneco.2023.106833.
60. Shetewy N, Shahin AI, Omri A, Dai K. Impact of financial development and internet use on export growth: New evidence from machine learning models. Res Int Bus Finance. 2022;61:101643. doi: https://doi.org/10.1016/j.ribaf.2022.101643.
61. Kumar S, Shukla AK:Muhuri K. and IEEE, Isolation Forest Based Multi-Source Unsupervised Transfer Learning for Missing GDP Prediction, 2020. doi: 10.1109/ijcnn48605.2020.9207482.
62. Bai Y, Yan C, Jiang F, Wei Y, Wang S. Exchange rate forecasting with macroeconomic data: Evidence from a novel comprehensive ensemble approach. J Int Money Finance. 2026;160:103446. doi: https://doi.org/10.1016/j.jimonfin.2025.103446.
63. Kutateladze V. The kernel trick for nonlinear factor modeling. Int J Forecast. 2022;38(1):165–177. doi: https://doi.org/10.1016/j.ijforecast.2021.05.002.
64. Price N and Atkinson PM. Global GDP Prediction With Night-Lights and Transfer Learning. IEEE J Sel Top Appl Earth Obs Remote Sens. 2022;15:7128–7138. doi: 10.1109/JSTARS.2022.3200754.
65. Theoharidis AF, Guillen DA, Lopes H. Deep learning models for inflation forecasting. Appl Stoch Models Bus Ind. 2023;39(3):447–470. doi: 10.1002/asmb.2757.
66. Shams MY, Tarek Z, El-kenawy E-SM, Eid MM, Elshewey AM. Predicting Gross Domestic Product (GDP) using a PC-LSTM-RNN model in urban profiling areas. Computational Urban Science. 2024;4(1). doi: 10.1007/s43762-024-00116-2.
67. Wang X, Li C, Yi C, Xu X, Wang J, Zhang Y. EcoForecast: An interpretable data-driven approach for short-term macroeconomic forecasting using N-BEATS neural network. Eng Appl Artif Intell. 2022;114. doi: 10.1016/j.engappai.2022.105072.
68. Hauzenberger N, Huber F, Klieber K. Real-time inflation forecasting using non-linear dimension reduction techniques. Int J Forecast. 2023;39(2):901–921. doi: https://doi.org/10.1016/j.ijforecast.2022.03.002.
69. Xiangyan P. Prediction Algorithm of Digital Economy Development Trend Based on Big Data. Math Probl Eng. 2022;2022. doi: 10.1155/2022/5025656.
70. Borup D, Rapach DE, Schütte ECM. Mixed-frequency machine learning: Nowcasting and backcasting weekly initial claims with daily internet search volume data. Int J Forecast. 2023;39(3):1122–1144. doi: https://doi.org/10.1016/j.ijforecast.2022.05.005.
71. Rolla LM and Giovannelli A. Macroeconomic forecasting using factor models with martingale difference errors. Int J Forecast. 2025. doi: https://doi.org/10.1016/j.ijforecast.2025.08.003.
72. Sengupta S, Chakraborty T, Singh SK. Forecasting CPI inflation under economic policy and geopolitical uncertainties. Int J Forecast. 2025;41(3):953–981. doi: https://doi.org/10.1016/j.ijforecast.2024.08.005.
73. Croushore D. Can you improve upon the GDP forecasts of professional forecasters using information about monetary

policy?. J Macroecon. 2025;86:103717. doi: https://doi.org/10.1016/j.jmacro.2025.103717.
74. Bessa G and Barbosa B. Integrating artificial intelligence into scenario analysis: a validated framework for strategic planning under economic uncertainty. Global Economics Research. 2025;1(2):100007. doi: https://doi.org/10.1016/j.ecores.2025.100007.
75. Simionescu M. Econometrics of sentiments- sentometrics and machine learning: The improvement of inflation predictions in Romania using sentiment analysis. Technol Forecast Soc Change. 2022;182:121867. doi: https://doi.org/10.1016/j.techfore.2022.121867.
76. Richardson A, van F. Mulder T, Vehbi T. Nowcasting GDP using machine-learning algorithms: A real-time assessment. Int J Forecast. 2021;37(2):941–948. doi: 10.1016/j.ijforecast.2020.10.005.
77. Rudd W, Bondell H, Silver J. Augmenting Neural Networks With Time-Varying Weights. J Forecast. 2025. doi: 10.1002/for.70014.
78. Adewale MD *et al.* Predicting gross domestic product using the ensemble machine learning method. Systems and Soft Computing. 2024;6:200132. doi: https://doi.org/10.1016/j.sasc.2024.200132.
79. Mirza N, Rizvi SKA, Naqvi B, Umar M. Inflation prediction in emerging economies: Machine learning and FX reserves integration for enhanced forecasting. International Review of Financial Analysis. 2024;94:103238. doi: https://doi.org/10.1016/j.irfa.2024.103238.
80. Zhao Y. Evaluation of the operational efficiency of internal capital markets in state-owned enterprises using big data. Financ Res Lett. 2025;85:108068. doi: https://doi.org/10.1016/j.frl.2025.108068.
81. Li Z, Zhu W, Wu Y, Wu Z. Reliability of analyst recommendations based on the DS-LightGBM model. Pacific-Basin Finance Journal. 2025;94:102961. doi: https://doi.org/10.1016/j.pacfin.2025.102961.
82. Di Domenico J, Catalano M, Riccetti L. Scaling and forecasting in a data-driven agent-based model: Applications to the Italian macroeconomy. Econ Model. 2025;147:107046. doi: https://doi.org/10.1016/j.econmod.2025.107046.
83. Sun W, Wang Y, Zhang L, Chen XH, Hoang YH. Enhancing economic cycle forecasting based on interpretable machine learning and news narrative sentiment. Technol Forecast Soc Change. 2025;215:124094. doi: https://doi.org/10.1016/j.techfore.2025.124094.
84. Ben Jabeur S and Serret V. Bankruptcy prediction using fuzzy convolutional neural networks. Res Int Bus Finance. 2023;64:101844. doi: https://doi.org/10.1016/j.ribaf.2022.101844.
85. Zhu F, Dong Y, Huang F. Data-rich economic forecasting for actuarial applications. Insur Math Econ. 2025;124:103126. doi: https://doi.org/10.1016/j.insmatheco.2025.103126.
86. Hauzenberger N, Huber F, Klieber K, Marcellino M. Bayesian neural networks for macroeconomic analysis. J Econom. 2025;249:105843. doi: https://doi.org/10.1016/j.jeconom.2024.105843.
87. Diakonova M, Molina L, Mueller H, Pérez JJ, Rauh C. The information content of conflict, social unrest and policy uncertainty measures for macroeconomic forecasting. Latin American Journal of Central Banking. 2024;5(4):100130. doi: https://doi.org/10.1016/j.latcb.2024.100130.
88. Alghamdi FM *et al.* Utilizing various statistical methods to model the impact of the COVID-19 pandemic on Gross domestic product. Alexandria Engineering Journal. 2024;97:204–214. doi: https://doi.org/10.1016/j.aej.2024.04.013.
89. Zhang Q, Ni H, Xu H. Nowcasting Chinese GDP in a data-rich environment: Lessons from machine learning algorithms. Econ Model. 2023;122:106204. doi: https://doi.org/10.1016/j.econmod.2023.106204.
90. Shahzad U, Si Mohammed K, Schneider N, Faggioni F, Papa A. GDP responses to supply chain disruptions in a post-pandemic era: Combination of DL and ANN outputs based on Google Trends. Technol Forecast Soc Change. 2023;192:122512. doi: https://doi.org/10.1016/j.techfore.2023.122512.
91. Anesti N, Kalamara E, Kapetanios G. Forecasting with Machine Learning methods and multiple large datasets. Econom Stat. 2024. doi: https://doi.org/10.1016/j.ecosta.2024.08.003.
92. Halawani HT *et al.* Attention Recurrent Neural Network With Earthworm Optimization on Gross Domestic Product Prediction using Main Economic Activities. Thermal Science. 2024;28(6B):5087–5095. doi: 10.2298/TSCI2406087H.
93. Zhou Y, Zhang Z, Guo Z. Explainable-machine-learning-based online transaction analysis of China property rights exchange capital market. International Review of Financial Analysis. 2025;102:104098. doi: https://doi.org/10.1016/j.irfa.2025.104098.
94. Monge M, Claudio-Quiroga G, Poza C. Chinese economic behavior in times of covid-19. A new leading economic indicator based on Google trends. International Economics. 2024;177:100462. doi: https://doi.org/10.1016/j.inteco.2023.100462.
95. Bolivar O. High-frequency inflation forecasting: A two-step machine learning methodology. Latin American Journal of Central Banking. 2025:100172. doi: https://doi.org/10.1016/j.latcb.2025.100172.
96. Thangjam A, Jaipuria S, Dadabada PK. Model selection for long-term load forecasting under uncertainty. Journal of Modelling in Management. 2024;19(6):2227–2247. doi: https://doi.org/10.1108/JM2-09-2023-0211.
97. Huber F, Koop G, Onorante L, Pfarrhofer M, Schreiner J. Nowcasting in a pandemic using non-parametric mixed frequency VARs. J Econom. 2023;232(1):52–69. doi: https://doi.org/10.1016/j.jeconom.2020.11.006.
98. Chen J, Tong K, Yu Q, Chen S, Balezentis T, Streimikiene D. Innovative knowledge-based system for forecasting daily hotel operations amid external events using multi-source data: A time-varying parameter state-space model. Journal of Innovation & Knowledge. 2026;11:100858. doi: https://doi.org/10.1016/j.jik.2025.100858.
99. Jiang H, Dong Y, Dong Y, Wang J. Probabilistic electricity price forecasting by integrating interpretable model. Technol Forecast Soc Change. 2025;210:123846. doi: https://doi.org/10.1016/j.techfore.2024.123846.
100. Costa EA, Silva ME, Galvão AB. Real-time nowcasting the monthly unemployment rates with daily Google Trends data. Socioecon Plann Sci. 2024;95:101963. doi: https://doi.org/10.1016/j.seps.2024.101963.
101. Wang Z, Zhu Z, Yu C. Variable Selection in Macroeconomic Forecasting with Many Predictors. Econom Stat. 2025;36:19–36. doi: https://doi.org/10.1016/j.ecosta.2023.01.003.
102. Woloszko N. Nowcasting with panels and alternative data: The OECD weekly tracker. Int J Forecast. 2024;40(4):1302–1335. doi: https://doi.org/10.1016/j.ijforecast.2023.11.005.
103. Song S, Chuang O-C, Fu H. Profitability of technical trading rules in the Chinese yuan-based foreign exchange market. Pacific-Basin Finance Journal. ;92:102804, 2025. doi: https://doi.org/10.1016/j.pacfin.2025.102804.

104. Deryugina E, Leonidov A, Ponomarenko A, Radionov S, Vasilyeva E. Network structure of the economy and the propagation of monetary shocks: The case of Russia. Structural Change and Economic Dynamics. 2024;71:315–319. doi: https://doi.org/10.1016/j.strueco.2024.08.006.
105. Liu Y and Swanson NR. An assessment of the marginal predictive content of economic uncertainty indexes and business conditions predictors. Int J Forecast. 2024;40(4):1391–1409. doi: https://doi.org/10.1016/j.ijforecast.2023.11.010.
106. Aaronson D, Brave SA, Butters RA, Fogarty M, Sacks DW, Seo B. Forecasting unemployment insurance claims in realtime with Google Trends. Int J Forecast. 2022;38(2):567–581. doi: https://doi.org/10.1016/j.ijforecast.2021.04.001.
107. Lu F, Ma F, Feng L. Carbon dioxide emissions and economic growth: New evidence from GDP forecasting. Technol Forecast Soc Change. 2024;205:123464. doi: https://doi.org/10.1016/j.techfore.2024.123464.
108. Lu F, Ma F, Hu S. Does energy consumption play a key role? Re-evaluating the energy consumption-economic growth nexus from GDP growth rates forecasting. Energy Econ. 2024;129:107268. doi: https://doi.org/10.1016/j.eneco.2023.107268.
109. Duan W, Khurshid A, Khan K, Calin AC. Transforming industry: Investigating 4.0 technologies for sustainable product evolution in china through a novel fuzzy three-way decision-making process. Technol Forecast Soc Change. 2024;200:123125. doi: https://doi.org/10.1016/j.techfore.2023.123125.
110. Hashimzade N, Kirsanov O, Kirsanova T. Integrating programming into the modern undergraduate economics curriculum. International Review of Economics Education. 2025;49:100310. doi: https://doi.org/10.1016/j.iree.2025.100310.
111. Ellwanger R and Snudden S. Putting VAR forecasts of the real price of crude oil to the test. Financ Res Lett. 2025;77:106940. doi: https://doi.org/10.1016/j.frl.2025.106940.
112. Lin H, Tao X, Wu C. Forecasting earnings with combination of analyst forecasts. J Empir Finance. 2022;68:133–159. doi: https://doi.org/10.1016/j.jempfin.2022.07.003.
113. Beheshtikhoo A, Pourgholi M, Khazaee I. Design of type-2 fuzzy logic controller in a smart home energy management system with a combination of renewable energy and an electric vehicle. Journal of Building Engineering. 2023;68:106097. doi: https://doi.org/10.1016/j.jobe.2023.106097.
114. Zhang Y, Wahab MIM, Wang Y. Forecasting crude oil market volatility using variable selection and common factor. Int J Forecast. 2023;39(1):486–502. doi: https://doi.org/10.1016/j.ijforecast.2021.12.013.
115. Wang W, Zhang Z, Wang L, Lan H, Xiong Y. Forecasting the market value of power battery industry chain: A novel RRMIDAS-SVR model. Journal of Management Science and Engineering. 2024;9(4):474–489. doi: https://doi.org/10.1016/j.jmse.2024.06.004.
116. Chen Q, Hong Y, Li H. Time-varying forecast combination for factor-augmented regressions with smooth structural changes. J Econom. 2024;240(1):105693. doi: https://doi.org/10.1016/j.jeconom.2024.105693.
117. Vandin A, Giachini D, Lamperti F, Chiaromonte F. Automated and distributed statistical analysis of economic agent-based models. J Econ Dyn Control. 2022;143:104458. doi: https://doi.org/10.1016/j.jedc.2022.104458.
118. Chini EZ. Can we estimate macroforecasters' mis-behavior?. J Econ Dyn Control. 2023;149:104632. doi: https://doi.org/10.1016/j.jedc.2023.104632.
119. Wan R, Fulop A, Li J. Real-time Bayesian learning and bond return predictability. J Econom. 2022;230(1):114–130. doi: https://doi.org/10.1016/j.jeconom.2020.04.052.
120. Napolitano L, Sbardella A, Consoli D, Barbieri N, Perruchas F. Green innovation and income inequality: A complex system analysis. Structural Change and Economic Dynamics. 2022;63:224–240. doi: https://doi.org/10.1016/j.strueco.2022.09.007.
121. Maung K and Swanson NR. A survey of models and methods used for forecasting when investing in financial markets. Int J Forecast. 2025;41(4):1355–1382. doi: https://doi.org/10.1016/j.ijforecast.2025.03.002.
122. Fadda P, Hanifi R, Istrefi K, Penalver A. Central bank communication of uncertainty. J Int Money Finance. 2025;157:103385. doi: https://doi.org/10.1016/j.jimonfin.2025.103385.
123. Chen B and Maung K. Time-varying forecast combination for high-dimensional data. J Econom. 2023;237(2, Part C):105418. doi: https://doi.org/10.1016/j.jeconom.2023.01.024.
124. Gefang D, Koop G, Poon A. Forecasting using variational Bayesian inference in large vector autoregressions with hierarchical shrinkage. Int J Forecast. 2023;39(1):346–363. doi: https://doi.org/10.1016/j.ijforecast.2021.11.012.
125. Zhang T, Tang K, Liu T, Jiang T. High frequency online inflation and term structure of interest rates: Evidence from China. J Empir Finance. 2025;83:101626. doi: https://doi.org/10.1016/j.jempfin.2025.101626.
126. Wang D,rée BPJ, Chamorro AF, Spencer PG. Transitions into and out of food insecurity: A probabilistic approach with panel data evidence from 15 countries. World Dev. 2022;159:106035. doi: https://doi.org/10.1016/j.worlddev.2022.106035.
127. Araújo GS and Gaglianone WP. Machine learning methods for inflation forecasting in Brazil: New contenders versus classical models. Latin American Journal of Central Banking. 2023;4(2). doi: 10.1016/j.latcb.2023.100087.
128. Dong Thi Ngoc L, Hoan ND, Nguyen H-N. Gross Domestic Product Forecasting Using Deep Learning Models with a Phase-Adaptive Attention Mechanism. Electronics (Switzerland). 2025;14(11) doi: 10.3390/electronics14112132.
129. Yu L, Zhao S, Liu C, Chen F. The acceleration and attenuation: Internet infrastructure and employment adjustment patterns. Structural Change and Economic Dynamics. 2025;75:726–743. doi: https://doi.org/10.1016/j.strueco.2025.10.003.
130. Park JS and Newaz MK. EU stock market integration: Policy impact and drivers. Economic Systems. 2025:101338. doi: https://doi.org/10.1016/j.ecosys.2025.101338.
131. Borup D, Christensen BJ, Mühlbach NS, Nielsen MS. Targeting predictors in random forest regression. Int J Forecast. 2023;39(2):841–868. doi: https://doi.org/10.1016/j.ijforecast.2022.02.010.
132. Quintero Gutiérrez LV, García Rendón J, Gutiérrez Gómez A. Impact of COVID-19 preventive measures on electricity demand: Evidence from Colombia. Socioecon Plann Sci. 2024;95:102025. doi: https://doi.org/10.1016/j.seps.2024.102025.
133. Zampella A and Ferri L. Steering through uncertainty: How organizational culture shapes earnings management. Financ Res Lett. 2025;85:107901. doi: https://doi.org/10.1016/j.frl.2025.107901.
134. Chen AY and McCoy J. Missing values handling for machine learning portfolios. J financ econ. 2024;155:103815. doi: https://doi.org/10.1016/j.jfineco.2024.103815.

135. Marahel AZ-. Essay in Climate Policy, Financial Econometrics and Machine Learning. 2025.
136. Wang RZ-. Essays in the Causal Inference and Economic Forecasting Using Machine Learning. 2020.
137. Chen J, Shen J, Ke N. Assessing the impact of new energy demonstration city policy on industrial carbon intensity using machine learning. Econ Anal Policy. 2025;87:1690–1707. doi: https://doi.org/10.1016/j.eap.2025.07.035.