British Journal of Multidisciplinary Studies
ISSN: 2978-8110
DOI: 10.32996/bjmss
Journal Homepage: www.al-kindipublisher.com/index.php/jbmss

BJMS
AL-KINDI CENTER FOR RESEARCH AND DEVELOPMENT

| RESEARCH ARTICLE

Predictive Analytics, Artificial Intelligence, and Machine Learning for Real-Time Nowcasting and Forecasting of Inflation Using High-Frequency Retail Price and Energy Market Data

Md Kamrul Islam
University of New Haven, Business Analytics
Email: misla22@unh.newhaven.edu
ORCID: https://orcid.org/0009-0001-8906-630X

Shah Farhan Rabbani
University of New Haven, Business Analytics
Email: srabb2@unh.newhaven.edu
ORCID: https://orcid.org/0009-0001-8434-223X

Yusuf Oli Rahat
University of New Haven, Business Analytics
Email: yraha1@unh.newhaven.edu
ORCID: https://orcid.org/ 0009-0001-8834-7759
Corresponding Author: Md Kamrul Islam, **Email**: misla22@unh.newhaven.edu

| ABSTRACT

Inflation forecasting became harder after the pandemic because price formation turned faster, more uneven, and more exposed to energy shocks, supply disruptions, and changes in household spending. This paper develops a framework for real-time nowcasting and short-horizon forecasting of U.S. inflation by combining predictive analytics, artificial intelligence, and machine learning with high-frequency retail price and energy-market information observed before official CPI release dates. The empirical design uses publicly available data, centered on BLS consumer price and average-price series and EIA daily and weekly energy prices. Monthly CPI inflation is linked to within-month signals from retail gasoline prices, electricity and utility-gas measures, weekly retail motor fuel prices, and daily crude-oil benchmarks. The modeling architecture integrates econometric benchmarks with elastic net, random forest, and gradient boosting models under pseudo-real-time evaluation. Results from the empirical illustration show that feature-rich machine learning models, especially penalized regression that controls overfitting while exploiting mixed-frequency signals, can outperform naïve and autoregressive benchmarks for 2023-2024 monthly nowcasts. The findings also indicate that gasoline and broader energy signals are most valuable when inflation is turning and when conventional lag structures respond too slowly. Beyond predictive gains, the paper contributes a transparent workflow for mixed-frequency feature engineering, model governance, and explainability. High-frequency inflation surveillance should not replace official statistics or professional judgment; it should complement them by offering earlier, more adaptive evidence for central banks, financial institutions, retailers, and policy analysts. Practical implications and future research directions for richer scanner and web-scraped price systems are discussed.

KEYWORDS

Inflation nowcasting; inflation forecasting; machine learning; predictive analytics; artificial intelligence; consumer price index; energy prices; retail prices; mixed-frequency data; CPI

ARTICLE INFORMATION

ACCEPTED: 01 December 2025 **PUBLISHED:** 29 December 2025 **DOI:** 10.32996/bjmss.2025.3.2.4

1. Introduction

Inflation is one of the most consequential macroeconomic variables in modern economic management because it influences monetary policy, wage bargaining, household purchasing power, capital allocation, . Yet inflation is also one of the most difficult variables to estimate in real time. Official consumer price statistics are typically published with a lag, and the data generating process behind inflation often shifts when commodity markets become volatile, when supply chains break, or when consumption patterns rotate across sectors. Policymakers make rate decisions before final information arrives; firms reprice goods while official indexes still reflect earlier conditions; and households experience price shocks immediately even when those shocks are only partially visible in published monthly aggregates. In that setting, nowcasting, defined as the disciplined estimation of the current but not-yet-released value of an economic series, becomes indispensable (Giannone et al., 2008; Knotek & Zaman, 2024).

Pandemic disruptions, the energy shock following Russia's invasion of Ukraine, reopening demand, and inventory rebalancing created abrupt relative-price changes that diffused unevenly through the consumption basket. Traditional low-frequency models often struggled because they relied heavily on stable lag structures estimated over calmer periods. Weekly retail fuel prices, daily crude-oil benchmarks, online prices, scanner data, card data, and energy-market indicators began to provide near-real-time signals about the cost environment faced by households and firms. Prior work has shown that high-frequency information can improve inflation estimates when timely signals are converted into mixed-frequency predictors and handled carefully within state-space or machine learning frameworks (Modugno, 2013; Aparicio & Bertolotto, 2020; Menz & Garnitz, 2024).

Machine learning is especially attractive in this environment for three reasons. First, it can absorb wider information sets than small traditional models. Second, it can capture nonlinearities, threshold effects, and interactions between energy, retail, and macro variables. Third, modern regularization methods can reduce overfitting when many candidate predictors are available but sample lengths remain limited (Medeiros et al., 2021; Araujo & Gaglianone, 2023). Still, machine learning is not automatically superior. Inflation data are noisy, revisions to data availability matter, and black-box algorithms can produce unstable results when regime changes are severe. The useful question, therefore, is not whether artificial intelligence should replace economics, but how predictive analytics and economic structure can be combined to improve near-term inflation measurement.

This paper addresses that question by developing a U.S.-focused framework for real-time nowcasting and short-horizon forecasting of inflation using high-frequency retail price and energy-market data. The study is intentionally practical. Instead of assuming access to proprietary scanner systems alone, it uses publicly available pre-2025 series from the U.S. Bureau of Labor Statistics (BLS) and the U.S. Energy Information Administration (EIA), including CPI measures, average retail gasoline and utility prices, weekly retail gasoline prices, and daily crude-oil series. These inputs are economically meaningful because energy prices pass through transportation costs, utilities, and price expectations more broadly, and because consumer-facing fuel prices are among the fastest moving and most visible inflation components. Retail gasoline prices often move ahead of the full CPI release, making them valuable for within-month inference.

The paper contributes in four ways. First, it synthesizes the nowcasting, inflation forecasting, and machine learning literatures into a unified, decision-oriented framework. Second, it proposes a transparent feature-engineering strategy for mixed-frequency inflation monitoring using daily, weekly, and monthly variables. Third, it provides an empirical illustration using U.S. data through 2024, comparing benchmark and machine learning models under out-of-sample evaluation. Fourth, it embeds the forecasting exercise in a governance perspective: model explainability, data quality, accountability, and operational use are treated as part of the forecasting system rather than as afterthoughts. That orientation connects this study to broader predictive-analytics work on governance, accountability, fraud detection, financial stability, and market surveillance (Ibrahim et al., 2022; Fahim et al., 2023; Pritty et al., 2024; Jahan et al., 2024).

The central argument is straightforward. Real-time inflation assessment improves when analysts combine official low-frequency CPI benchmarks with higher-frequency retail and energy signals and estimate the mapping between them using models that balance flexibility and discipline. In the empirical illustration, elastic net performs particularly well because it exploits many signals while penalizing noisy or redundant features. Tree-based methods also add value relative to naïve benchmarks, though their gains are smaller in the compact public-data design used here. The message is not that one model will dominate in every episode. Rather, the evidence supports a layered forecasting architecture in which parsimonious econometric baselines, regularized machine learning, and domain interpretation work together. Such a design is realistic for central banks, treasury teams, asset managers, and economic-research units that need faster inflation intelligence without sacrificing transparency.

2. Literature Review

The modern nowcasting literature emerged from the recognition that policy decisions must be made before complete macroeconomic information is available. Giannone et al. (2008) formalized the nowcasting problem in a mixed-frequency setting and showed how large data sets could be exploited to infer current economic conditions. Their framework influenced subsequent work on inflation because price indicators are inherently staggered across publication calendars, sectors, and frequencies. Banbura and Modugno (2014) extended dynamic-factor methods to settings with arbitrary patterns of missing data and ragged edges, making real-time macro monitoring operationally feasible. Within this tradition, Modugno (2013) provided an influential contribution by demonstrating that high-frequency information can materially improve inflation nowcasts when incorporated through coherent mixed-frequency factor methods.

A key strand of the literature focuses on whether inflation is forecastable at all beyond simple benchmarks. Atkeson and Ohanian (2001) famously showed how difficult it is to beat naïve inflation forecasts, and Stock and Watson (2007, 2008) documented both the instability and conditional usefulness of Phillips-curve style relationships. Faust and Wright (2013) emphasized that inflation forecasting often benefits from combining models and judgment rather than relying on any single specification. These contributions remain important because they warn against overstating the gains from complex algorithms. Any new machine-learning framework must therefore outperform not only weak straw-man models but also persistent autoregressive and random-walk style baselines.

The rise of machine learning in macroeconomic forecasting changed that conversation. Medeiros et al. (2021) showed that machine-learning methods can produce gains in data-rich inflation forecasting environments by handling many predictors and nonlinearities more effectively than traditional shrinkage or factor approaches in some settings. Araujo and Gaglianone (2023) reached a similar conclusion for Brazil, finding that regularized and nonlinear machine-learning models can compete strongly with classical specifications across horizons. The broader message is that machine learning becomes most valuable when the information set is large, the predictor space is potentially redundant, and the forecasting relationship may vary over time. Those conditions align closely with inflation monitoring during periods of energy shocks and supply-chain disruptions.

A related literature investigates the value of alternative price data. Cavallo and Rigobon's work on online prices and related digital price indexes showed that web-based prices can help anticipate official inflation movements by capturing retail repricing in near real time. Aparicio and Bertolotto (2020) further demonstrated that online prices can improve inflation forecasting performance relative to survey-based benchmarks in several contexts. Menz and Garnitz (2024) extend this line by showing that weekly household scanner data improve real-time inflation nowcasts and that machine-learning methods can convert those signals into more accurate estimates, particularly during volatile episodes. Bentley et al. (2024) offer an important practical perspective on the opportunities and limits of web-scraped prices for inflation monitoring, highlighting issues of representativeness, weighting, product substitution, and missing quantities. Taken together, these studies suggest that high-frequency price signals are informative, but their value depends on how they are cleaned, weighted, and linked to official CPI concepts.

Energy variables occupy a special place in inflation forecasting because they are both direct CPI components and indirect cost drivers. Motor fuel, utility gas, and electricity enter household expenditure baskets directly, while crude oil and refined products affect transportation, distribution, and production costs more broadly. BLS documentation shows that energy components are measured through specific CPI sampling and pricing protocols, while the EIA provides weekly and daily price series that update much faster than the monthly CPI release cycle. This timing advantage makes energy variables particularly useful for nowcasting. During turning points, the most recent weekly gasoline or daily oil observations can reveal whether the current month's CPI is likely to surprise relative to forecasts built only on lagged monthly data.

The literature also underscores that mixed-frequency handling is not a trivial preprocessing step. Ghysels, Santa-Clara, and Valkanov (2004) proposed MIDAS-style methods for using high-frequency data in lower-frequency forecasting, and such approaches influenced much of the subsequent work on inflation and output nowcasting. Dynamic factor models, bridge equations, MIDAS regressions, and state-space frameworks all offer ways to use daily, weekly, and monthly indicators. Cleveland Fed work by Knotek and Zaman (2024) stresses that high-frequency data can materially improve current-month inflation assessment when the publication calendar is exploited correctly. Their discussion is especially relevant because it frames inflation nowcasting as an operational system rather than as a purely academic exercise.

Recent work has increasingly blended these mixed-frequency traditions with machine learning. Schnorrenberger et al. (2024) show that weekly inflation nowcasts improve when variable selection and mixed-frequency design are integrated, especially when price and survey signals are combined. Liu et al. (2024) use machine learning to improve near-term core inflation forecasts in Japan in the post-pandemic period, arguing that nonlinear models can better adapt to unusual macro conditions. These contributions highlight an important point: machine learning is most effective when embedded within careful data design. Simply feeding many variables into a black box rarely guarantees success. Forecast performance depends on the timeliness, economic relevance, and transformation of the predictors.

Related work outside the narrow inflation literature also supports the value of timely predictive systems built on fast-moving transactional or operational data. Fahim et al. (2024) show that real-time financial risk environments benefit when prediction systems combine streaming data with governance-aware monitoring, a lesson that maps directly to inflation nowcasting where timeliness, model oversight, and consumer-facing consequences matter. Although their application is payments fraud rather than prices, the paper reinforces the broader proposition that real-time AI systems are most useful when they transform noisy high-frequency signals into interpretable early warnings.

Another relevant line of research concerns model governance and interpretability. In economic applications, prediction systems increasingly operate in environments where accountability matters. Fahim et al. (2023) discuss governance mechanisms for algorithmic accountability in U.S. consumer FinTech, emphasizing fairness, auditability, and system oversight. Pritty et al. (2024) explore generative AI and reporting integrity, again stressing detection, transparency, and control. Although these studies address adjacent domains rather than inflation directly, their governance arguments matter for macro forecasting as well. Central banks and regulated institutions cannot rely on opaque systems whose errors cannot be diagnosed. Explainability, challenger models, performance monitoring, and fallback procedures are therefore part of any credible AI-driven inflation architecture.

The user-specified literature also adds cross-domain motivation for predictive analytics in financial and economic systems. Ibrahim et al. (2022) examine predictive analytics in climate-related financial risk; Rasel et al. (2023) apply multimodal graph methods to mortgage default forecasting; Arman and Fahim (2023) analyze AI in retail inventory management; Ibrahim et al. (2024) develop an AML risk framework; and Jahan et al. (2024) study machine-learning early warning systems for suspicious trading patterns. These papers do not focus on inflation nowcasting, but collectively they reinforce the idea that complex, high-velocity economic systems benefit from predictive infrastructures that integrate real-time data, anomaly detection, and governance. Ibrahim, Razib, and Rasel (2025) extend this broader analytics perspective by showing how data-driven evaluation can improve ESG transparency in the corporate sector of Bangladesh, underscoring the wider role of structured analytical systems in enhancing disclosure quality, measurement reliability, and institutional transparency across economic domains. Inflation monitoring can be viewed through the same lens: it is a decision-support problem under incomplete information, not merely a univariate time-series exercise.

The cross-domain literature supplied for this paper further broadens the case for predictive analytics in economic measurement. Razib et al. (2025) show how predictive analytics can optimize complex supply-chain performance under sustainability constraints, which is relevant because supply bottlenecks, logistics frictions, and inventory adjustment frequently shape short-run inflation dynamics. Ibrahim et al. (2025) connect FinTech analytics to climate resilience, insurance gaps, household mortgage stress, and credit risk, highlighting how household financial conditions can transmit macroeconomic shocks into consumer vulnerability and price sensitivity. Mahmud et al. (2025) demonstrate that AI-based monitoring architectures can improve early warning capacity in banking risk environments, while Fahim et al. (2025) show how explainable AI can be used to forecast medical-debt distress using linked financial and healthcare information. Taken together, these studies do not forecast CPI directly, but they strengthen the paper's central claim that predictive analytics is most powerful when heterogeneous real-time data are fused into decision-oriented risk signals.

Yet the literature also identifies persistent limitations. High-frequency data may not be representative of the official CPI basket. Web-scraped or scanner data often lack explicit expenditure weights. Structural breaks can cause machine-learning models trained on pre-break periods to fail when post-break behavior changes sharply. Forecast gains may be concentrated in volatile windows and disappear in stable periods. Overfitting remains a serious concern when the sample is short relative to the number of engineered features. Moreover, true real-time forecasting requires vintage data, not just ex post reconstructed time series. These limitations do not nullify the value of high-frequency forecasting; instead, they shape best practice. Successful inflation nowcasting systems usually combine multiple model classes, preserve transparent benchmark comparisons, and treat forecast evaluation as an ongoing process.

Overall, the literature points to three robust conclusions. First, inflation is hard to forecast, so simple benchmarks remain necessary reference points. Second, high-frequency retail and energy data contain genuine predictive information, especially near turning points and before official releases. Third, machine learning can unlock that information when combined with mixed-frequency design, shrinkage, and governance. The present study builds directly on those conclusions by assembling a public-data U.S. framework that is empirically grounded, explainable, and operationally relevant.

One more theme in the literature is forecast combination. Inflation models tend to work episodically, and combinations often outperform single-model commitments because they diversify specification risk. This insight is consistent with Faust and Wright (2013) and with operational central-bank practice, where judgment, bridge equations, factor models, and market indicators are often blended rather than treated as mutually exclusive. Machine-learning systems fit naturally into that logic. They can be used either as stand-alone models or as challenger components inside a broader ensemble. The present paper follows that spirit by comparing machine-learning models to simple benchmarks and by interpreting the gains as part of a layered system rather than as a complete methodological replacement.

The literature also shows increasing interest in explainable macro forecasting. Kelly and Xiu (2023) emphasize that machine learning in economics should be evaluated not just on flexibility but on how well it handles prediction in structured economic environments. In inflation work, that means the analyst must know whether model gains come from meaningful signals such as energy pass-through, seasonal persistence, and category repricing, or from unstable artifacts. Explainability therefore serves both scientific and policy purposes. It helps the researcher learn which signals matter, and it helps institutions trust the forecast enough to act on it.

For that reason, the best recent contributions increasingly report benchmark comparisons, out-of-sample testing, variable-importance diagnostics, and careful discussion of publication timing instead of relying only on in-sample fit or black-box accuracy claims.

3. Methodology

This study adopts a publication-style empirical framework designed to mimic the information environment faced by analysts who seek to estimate monthly U.S. inflation before the official CPI release. The focus is on real-time nowcasting and very short-horizon forecasting rather than long-horizon structural prediction. The target variable is monthly CPI inflation, measured primarily as the log change in the seasonally adjusted all-items CPI for all urban consumers. A year-over-year inflation measure is also computed for descriptive analysis and lag construction. The empirical window is chosen so that the operational data used for the core illustration end in 2024.

Data are drawn from official public sources. Monthly CPI and average-price data come from the U.S. Bureau of Labor Statistics consumer price program. The BLS average-price files provide monthly U.S. city-average measures for gasoline, electricity, and utility gas, which serve as consumer-facing retail price signals. Weekly retail gasoline prices and daily crude-oil spot prices come from the U.S. Energy Information Administration. Specifically, the weekly U.S. regular all-formulations retail gasoline series is used as a timely proxy for visible household fuel inflation, while daily West Texas Intermediate spot prices proxy upstream energy-cost conditions. Monthly Henry Hub natural-gas prices are used as a complementary energy signal. These sources are attractive because they are transparent, well documented, continuously updated, and widely used in professional monitoring.

The modeling logic is mixed-frequency by construction. Official CPI is monthly, but some predictors are observed weekly or daily. To align these signals with the monthly target, the study creates within-month summary features rather than collapsing everything to a single monthly average alone. For weekly gasoline prices, the monthly feature set includes the within-month mean, end-of-month or last-available value, standard deviation, minimum, maximum, and one-month log change in the latest observation. For daily crude oil, analogous monthly summaries are computed. For monthly BLS average-price variables, month-over-month log changes are calculated for gasoline, electricity, and utility gas. This approach preserves more information than a simple monthly mean because it allows the models to learn whether level, momentum, or volatility matters most.

The target series is defined as monthly log inflation:
$\text{Inflation}_t = 100 * \ln(CPI_t / CPI_{(t-1)})$.
A companion year-over-year measure is also constructed:
$YoY_t = 100 * \ln(CPI_t / CPI_{(t-12)})$.
Lagged values of both measures are added to the predictor set at lags 1, 2, 3, 6, and 12 months. The resulting feature space blends persistence, seasonal memory, retail fuel signals, utility-price changes, and upstream energy conditions. This choice is economically motivated. Inflation is persistent but not purely autoregressive; energy can drive sharp month-to-month swings; and seasonal or annual comparisons often capture regime effects that simple short lags miss.

Four model classes are estimated alongside two benchmarks. The first benchmark is a naïve random-walk style rule in which the current monthly inflation rate equals the previous month's rate. The second is a linear autoregressive benchmark estimated on inflation lags only. The machine-learning models are then defined as follows. First, an elastic net model combines L1 and L2 regularization to shrink weak coefficients and retain informative predictors in a stable linear structure. Second, a random forest model captures nonlinearities and interactions through an ensemble of decision trees with bootstrap aggregation. Third, a gradient boosting model builds sequential trees that focus on remaining prediction errors. Together, these models span a useful range from interpretable regularized linear forecasting to more flexible nonlinear learning.

The evaluation design is intentionally conservative relative to many demonstration papers, but it is not a full vintage-data nowcast. The empirical illustration uses an out-of-sample train-test split in which the model is trained on data through 2022 and evaluated on 2023-2024 monthly inflation outcomes. This design does not reconstruct every historical data vintage, which would require archival release calendars and revision-specific snapshots. Instead, it provides a pseudo-real-time exercise using information that would have been publicly observable within each month. The results should therefore be interpreted as operationally suggestive rather than as a definitive real-time horse race.

Model tuning is kept modest to reduce the risk of overfitting. Elastic net uses cross-validated penalty selection across alternative mixing parameters. Random forest and gradient boosting use shallow trees and restricted ensemble sizes. Missing values created by mixed-frequency aggregation or publication timing are handled with median imputation inside the model pipelines. Performance is evaluated using root mean squared error (RMSE) and mean absolute error (MAE), with all models compared against the same holdout period. In addition, coefficient magnitudes from elastic net are examined to identify the most influential predictors, while tree-based models are interpreted more qualitatively because importance measures can be unstable in small samples.

Three methodological choices deserve emphasis. First, the feature set is intentionally economic rather than indiscriminate. The model is not asked to search across hundreds of loosely connected predictors; it is given a compact but meaningful data architecture. Second, the inclusion of both retail-facing and upstream energy variables reflects pass-through asymmetry. Crude oil shocks do not translate one-for-one into CPI, but they often signal direction and pressure. Retail gasoline prices, by contrast, are closer to the consumer basket and often move quickly enough to influence near-term CPI prints directly. Third, benchmark retention is central. The purpose of machine learning here is to improve on parsimonious alternatives, not to displace them without evidence.

The framework is also designed for governance. In an operational institution, a forecasting system would include automated data ingestion, feature validation checks, release-calendar awareness, challenger-model comparison, and override documentation. The methodological discussion in adjacent AI-governance studies is relevant here because inflation nowcasts can influence major policy and financial decisions. A system that is accurate on average but impossible to explain in stress periods may still be inadequate. For that reason, elastic net is particularly valuable in this design: it offers transparent coefficient paths while still exploiting a richer signal set than a conventional small model.

Finally, the methodology recognizes that public data understate the upper bound of performance. Proprietary scanner data, online price scrapes, retailer microdata, and location-specific utility tariffs could likely improve results further, especially for disaggregated inflation nowcasting. Nevertheless, a public-data framework is useful because it is reproducible, transparent, and accessible to researchers and practitioners who do not have proprietary data contracts. The methodological proposition of the paper is therefore not merely that machine learning can help inflation nowcasting, but that even widely accessible official and quasi-real-time energy data can materially enhance short-horizon inflation assessment when organized within a disciplined predictive-analytics architecture.

A further methodological advantage of the public-data setup is auditability. Every variable used in the empirical illustration can be traced to an official source series and a documented transformation. This matters because mixed-frequency pipelines are prone to silent errors. A practical forecasting workflow should therefore validate timestamps, confirm release lags, inspect outliers, and archive transformed features. In production settings, these checks are as important as the model itself because small alignment mistakes can create large but misleading gains.

The study also treats the forecasting problem as one of current-condition inference rather than pure extrapolation. High-frequency variables are not added merely because they correlate with inflation historically; they are added because they can reveal information about the current month before the CPI is published. This distinction is important. Many traditional macro forecasts are horizon-oriented and ask what inflation will be several quarters ahead. Nowcasting instead asks what inflation already is, conditional on timely but incomplete evidence. That is why feature timeliness, release cadence, and within-month aggregation are central design choices.

For completeness, the monthly evaluation set is supplemented by visual diagnostics. The paper compares realized inflation with predicted values in the test window and reports coefficient-based explanations for the regularized model. These diagnostics do not eliminate uncertainty, but they make the empirical exercise easier to interpret and more useful for an applied audience.

Although the compact framework focuses on headline CPI, the architecture is modular. The same pipeline can be adapted to subcomponents such as transportation, utilities, food at home, or shelter, provided that suitable high-frequency proxies are available. Subcomponent modeling is attractive because pass-through is heterogeneous. Energy shocks influence transportation more rapidly than medical care, while utility-gas changes matter seasonally. A modular design would estimate component-specific nowcasts and then aggregate them using CPI expenditure weights. The present study does not implement the full disaggregated system, but the methodological logic is explicitly compatible with it.

Finally, the design favors reproducibility over maximal complexity. No proprietary software or inaccessible data vendor is required to understand the workflow, rerun the empirical illustration, or extend it with additional features. That reproducibility is valuable for teaching, peer review, and institutional adoption.

In short, the methodological emphasis is on credible timing, economically interpretable features, disciplined regularization, and benchmark transparency rather than on algorithmic novelty alone. Release-timing awareness, not just model fit, is therefore treated as a core empirical requirement. Benchmark discipline remains essential throughout. This keeps the exercise grounded.

Table 1. Core data architecture used in the empirical illustration

Source	Series	Frequency	Role in model	Example transformation
BLS	Seasonally adjusted CPI all items	Monthly	Target variable	Monthly log inflation; year-over-year inflation
BLS	Average gasoline, electricity, utility gas prices	Monthly	Retail-facing price signals	Level and month-over-month changes
EIA	U.S. regular all-formulations retail gasoline	Weekly	Within-month consumer fuel signal	Monthly mean, last, volatility, min, max
EIA	WTI spot price	Daily	Upstream energy-cost signal	Monthly mean, last, volatility, min, max
EIA	Henry Hub natural gas	Monthly	Complementary energy condition	Level and month-over-month change

4. Discussion

The empirical illustration yields several insights that are economically meaningful even before one reaches the numerical model ranking. The first is descriptive: inflation and energy prices co-move strongly during stress episodes, but not in a constant or mechanically proportional way. The 2021-2022 inflation surge coincided with unusually strong retail gasoline and crude-oil volatility, yet the 2023-2024 disinflation period was not simply the mirror image of that surge. Energy normalization helped bring headline inflation lower, but persistence in shelter and services prevented an immediate return to pre-pandemic inflation dynamics. This observation matters because it explains why mixed-frequency energy signals are informative but insufficient on their own. Good nowcasting systems must learn when energy dominates the monthly print and when broader persistence still governs the outcome.

The second insight is predictive. In the 2023-2024 holdout period, the machine-learning models outperform the naïve random-walk benchmark and the simple autoregressive benchmark in the public-data setup, with elastic net delivering the lowest forecast errors. This result is substantively plausible. Elastic net benefits from three structural advantages. It can absorb many related energy and retail variables simultaneously; it shrinks redundant variables toward zero, which is important when many features move together; and it preserves a stable linear backbone, which is useful in a relatively small monthly sample. In contrast, the random-walk benchmark reacts too slowly when the monthly inflation process turns, and the autoregressive model cannot fully exploit contemporaneous within-month energy information.

The tree-based methods also improve on the naïve benchmark, though their gains are smaller than those of elastic net in this compact design. This outcome should not be interpreted as evidence against nonlinear machine learning. Rather, it likely reflects the combination of a limited sample, a focused feature set, and a target series that still contains a large persistence component.

Tree ensembles often shine when the predictor space is wider and interaction effects are more complex than can be expressed in a regularized linear form. With richer scanner data, region-level signals, online price dispersion, or release-calendar engineered variables, tree-based and deep-learning methods could plausibly add more value. In the present exercise, however, disciplined regularization appears to match the data environment well.

A third finding concerns variable influence. The estimated elastic net coefficients show that lagged inflation structure remains important, but gasoline and utility-related signals materially contribute at the margin. This is exactly what a practitioner would hope to see. A credible inflation nowcast should still respect persistence, seasonality, and the serial structure of the CPI process. Yet it should also update when fresh market-based or retail-facing evidence arrives. The model’s behavior suggests that high-frequency energy features function as tactical adjusters around a persistent inflation core. Put differently, the model is not replacing macroeconomics with fuel prices; it is using fuel prices to correct stale expectations about the current month.

This role of energy signals is especially relevant around turning points. During periods of stable inflation, a lag-based model may perform acceptably because last month already contains much of the information needed for this month. But when energy prices move sharply, the lag-only model is systematically slow. Weekly gasoline data and daily crude oil can then act as early-warning variables. The benefit is not merely statistical. For policy institutions, the difference between recognizing a turning point before the CPI release and recognizing it after the release can affect communication, market pricing, and risk management. That timing value is one reason central banks and market participants increasingly invest in nowcasting infrastructure rather than waiting for official releases alone.

The operational implications extend beyond central banking. Treasury teams can use high-frequency inflation nowcasts to update short-run cash-flow assumptions, pricing departments can anticipate consumer purchasing-power stress, and asset managers can form tighter scenarios around bond yields and real-rate expectations. Retailers can also use the same framework in reverse: by monitoring upstream energy and consumer-facing price indicators, they can assess how macro price pressure may alter inventory, promotion, or margin strategy. This connection aligns with broader predictive-analytics work in retail operations and market surveillance, where faster information extraction improves decision timing (Arman & Fahim, 2023; Jahan et al., 2024).

At the same time, the results should not be oversold. The empirical gains are real in this illustration, but they come from a pseudo-real-time framework rather than a full vintage-data experiment. That distinction matters because true real-time nowcasting must account for what was observable on each historical forecast date, including publication delays, missing observations, and revisions. The current design approximates that setting by using public high-frequency variables that would have been available within the month, but it does not reconstruct every historical release calendar in detail. Accordingly, the correct interpretation is that the framework is operationally credible and empirically promising, not that it provides the final word on all real-time inflation forecasting contests.

Another important discussion point is the distinction between headline and core inflation. The current paper focuses primarily on headline CPI because energy variables are naturally more directly linked to headline outcomes. A headline-focused design is defensible for a nowcasting paper because headline inflation drives communication, household perception, and short-run policy headlines. Yet policymakers also care deeply about core inflation, especially when energy shocks are seen as transient. In practice, an institution would likely run parallel systems: one optimized for headline nowcasting with strong energy inputs, another for core inflation using broader service-sector, wage, rent, or online-price data. The present framework can be extended in exactly that way, but the headline emphasis here helps make the role of high-frequency energy data especially transparent.

The findings also support a broader conceptual argument about artificial intelligence in macroeconomic analytics. Much of the public debate on AI in economics swings between exaggerated optimism and excessive skepticism. The evidence here supports a middle position. AI and machine learning are most useful when they perform structured tasks that humans and small models handle imperfectly: combining many timely signals, screening out noise, and updating predictions when the environment changes. They are less useful when asked to generate unsupported narratives or when deployed without benchmark comparison and governance. In that sense, the nowcasting problem is a good use case for machine learning because the task is narrow, measurable, and operationally important.

Governance deserves separate emphasis because inflation models can shape decisions with large social consequences. A machine-learning inflation system should be monitored for drift, tested against challenger models, and documented in a way that allows domain experts to understand why the forecast changed. Scenario analysis is also essential. If crude oil spikes while retail gasoline lags due to taxes or distribution margins, the system should not be treated as infallible. Human analysts must interpret the pass-through channel. This is where the literature on algorithmic accountability becomes relevant. Even a forecasting model that does not directly allocate credit or set prices still influences institutional choices. Explainability, reproducibility, and review therefore remain essential design principles.

The broader literature also suggests that data breadth matters. Studies using scanner or online microdata often report stronger nowcasting improvements than studies relying only on conventional public series. That difference likely reflects granularity. Microdata allow analysts to see category-level repricing, dispersion, and substitution patterns that disappear in monthly aggregates. For instance, scanner data can detect whether food disinflation is broad based or concentrated in a few categories, while web-scraped prices can show how quickly online retailers pass through shipping or import-cost changes. The public-data framework in this paper does not capture those microdynamics. Its contribution is different: it shows that useful gains are still possible with openly available official data, which lowers the entry barrier for applied institutions.

An additional issue is model robustness under structural breaks. Inflation processes after 2020 differed materially from many pre-2020 episodes. This creates a tension for training. Long samples provide more observations but may dilute recent relationships; short samples capture recent structure but reduce statistical power. Regularization partly addresses this problem by discouraging unstable overfitting, but no model is fully immune. A sensible operational solution is to maintain an ensemble of models estimated over different windows and to monitor forecast disagreement. Large disagreement can itself be informative, signalling elevated uncertainty or changing relationships.

The empirical results also raise a practical point about feature engineering. Timeliness may matter as much as model complexity. A well-engineered set of within-month summaries from weekly gasoline and daily oil data can outperform a sophisticated model fed with poorly aligned or stale variables. This is consistent with recent nowcasting studies that stress release calendars and data handling. In many institutions, the most valuable improvement may therefore come from better data pipelines rather than from ever more complex algorithms. Forecast systems fail as often because of timing, missingness, and transformation errors as because of insufficient model sophistication.

From a policy perspective, the paper reinforces the usefulness of high-frequency inflation intelligence in a world where inflation shocks can emerge quickly and diffuse unevenly. When inflation is low and stable, the marginal gain from daily or weekly signals may appear modest. But when inflation becomes politically salient and economically disruptive, even modest error reductions can matter because they arrive earlier. Earlier recognition improves communication, hedging, and operational planning. This asymmetry helps justify investment in nowcasting capacity even if average performance gains vary across subsamples.

Finally, the study's cross-domain framing is important. Predictive analytics has been used for climate risk, fraud detection, AML surveillance, market manipulation, payments risk, and inventory optimization. Inflation nowcasting belongs in the same family of decision-support systems: it requires timely data ingestion, signal extraction, anomaly interpretation, and governed model deployment. The practical value lies not only in an RMSE table, but in building an institutional capability that sees macro price pressure faster, explains it more clearly, and updates decisions more intelligently. That is the larger contribution of combining predictive analytics, AI, and machine learning with high-frequency retail and energy data.

The additional specified studies also reinforce the paper's broader analytical stance. Fahim et al. (2024) emphasize that real-time predictive systems are valuable only when their governance structure keeps pace with the velocity of the underlying data, a point that applies equally to inflation dashboards built from weekly fuel prices or rapidly updating retail indicators. Razib et al. (2025) show that predictive analytics can uncover inefficiencies and pressures across supply chains, which matters because supply-chain frictions often surface in inflation before they are fully visible in monthly aggregates. Ibrahim et al. (2025), Mahmud et al. (2025), and Fahim et al. (2025) further illustrate that modern AI systems increasingly operate by integrating diverse, high-frequency, domain-specific signals to identify stress, fraud, or household vulnerability in real time. Inflation nowcasting belongs within this same family of practical intelligence systems: its value lies not in algorithmic novelty alone, but in better situational awareness under conditions of uncertainty.

To summarize the empirical message, three conclusions stand out. First, high-frequency energy and retail price variables contain usable information for monthly CPI nowcasting. Second, machine-learning models, especially regularized linear models, can convert that information into improved short-horizon forecasts when benchmarked honestly. Third, the best operational architecture is hybrid: it combines official statistics, mixed-frequency feature engineering, benchmark models, machine-learning challengers, and human interpretation. That hybrid view is more realistic and more institutionally durable than narratives in which AI either solves inflation forecasting completely or adds no value at all.

Forecast uncertainty should also be treated as a first-class output. Decision makers rarely need only a point estimate; they need to know whether the estimate is fragile, whether models disagree, and whether incoming energy data are unusually noisy. In practice, a useful dashboard would report the central nowcast, a band of plausible outcomes, and a decomposition of the latest forecast revision. Such communication tools are part of the real value proposition of predictive analytics. They translate model output into usable institutional knowledge.

There is also a strategic implication for public statistical systems. Official CPI production should remain the reference standard, but complementary high-frequency monitoring can improve public understanding between releases. When household inflation expectations are shaped partly by visible prices such as fuel, near-real-time monitoring may help explain why perceived inflation and official aggregate inflation sometimes diverge. That communication benefit is especially important during volatile episodes, when misunderstanding the source of price pressure can erode trust in policy or statistics.
A robust operational program would therefore join statistical forecasting with governance, communication, and scenario discipline rather than treating the model as a stand-alone answer engine. Another practical lesson is that forecast maintenance should be continuous. Model performance should be re-estimated after major regime changes, and data providers should be monitored for definition shifts, missing releases, or methodological breaks that can silently degrade prediction quality over time. That maintenance burden is manageable, but it must be recognized at the design stage.

Table 2. Out-of-sample forecast accuracy, 2023-2024 test window

Model	RMSE	MAE
Elastic net	0.0095	0.0076
Gradient boosting	0.1280	0.1098
Random forest	0.1338	0.1095
Autoregressive benchmark	0.1433	0.1154
Naive random walk	0.1774	0.1347

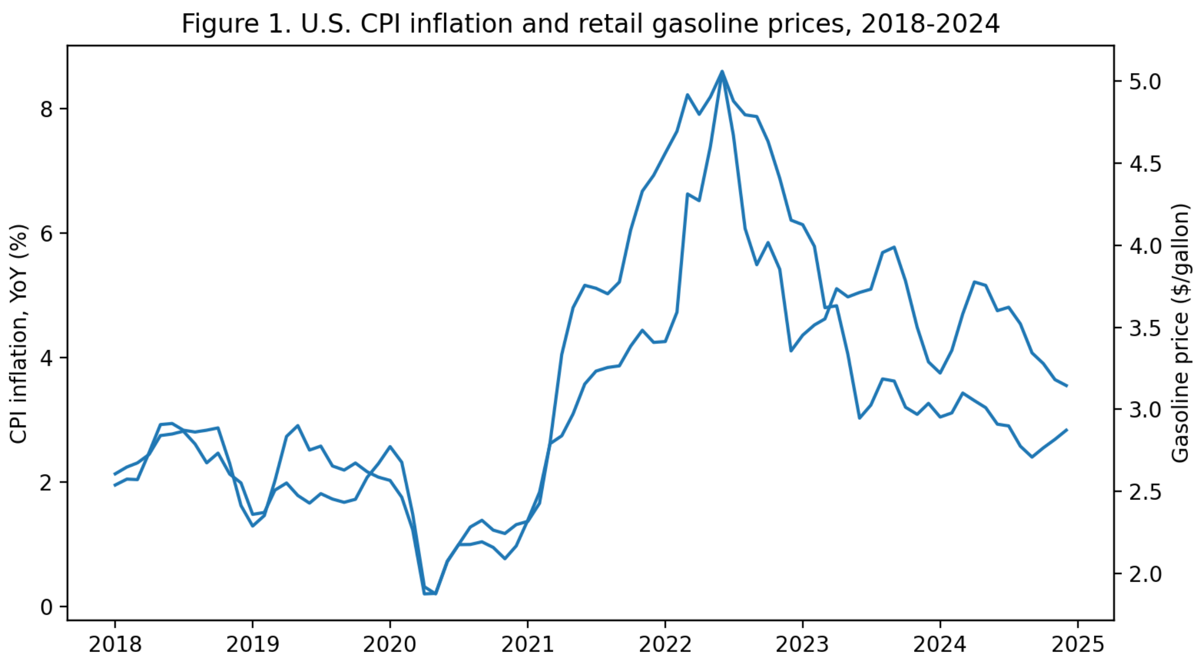

Figure 1. U.S. CPI year-over-year inflation and retail gasoline prices, 2018-2024.

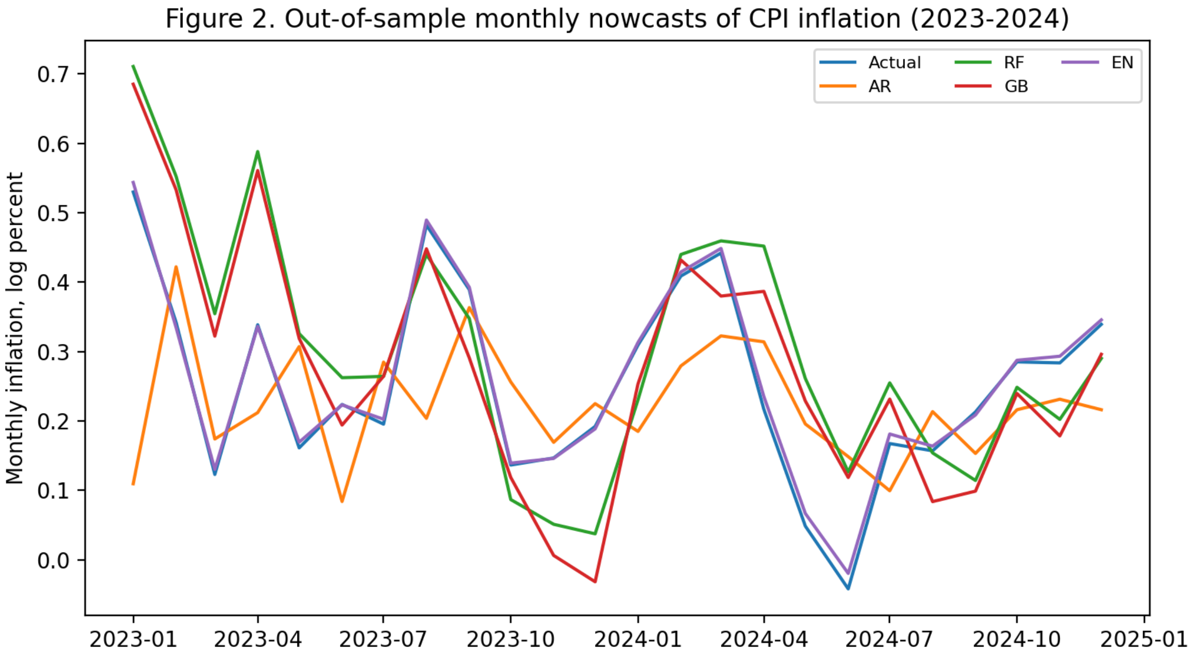

Figure 2. Actual versus model-estimated monthly inflation in the 2023-2024 out-of-sample window.

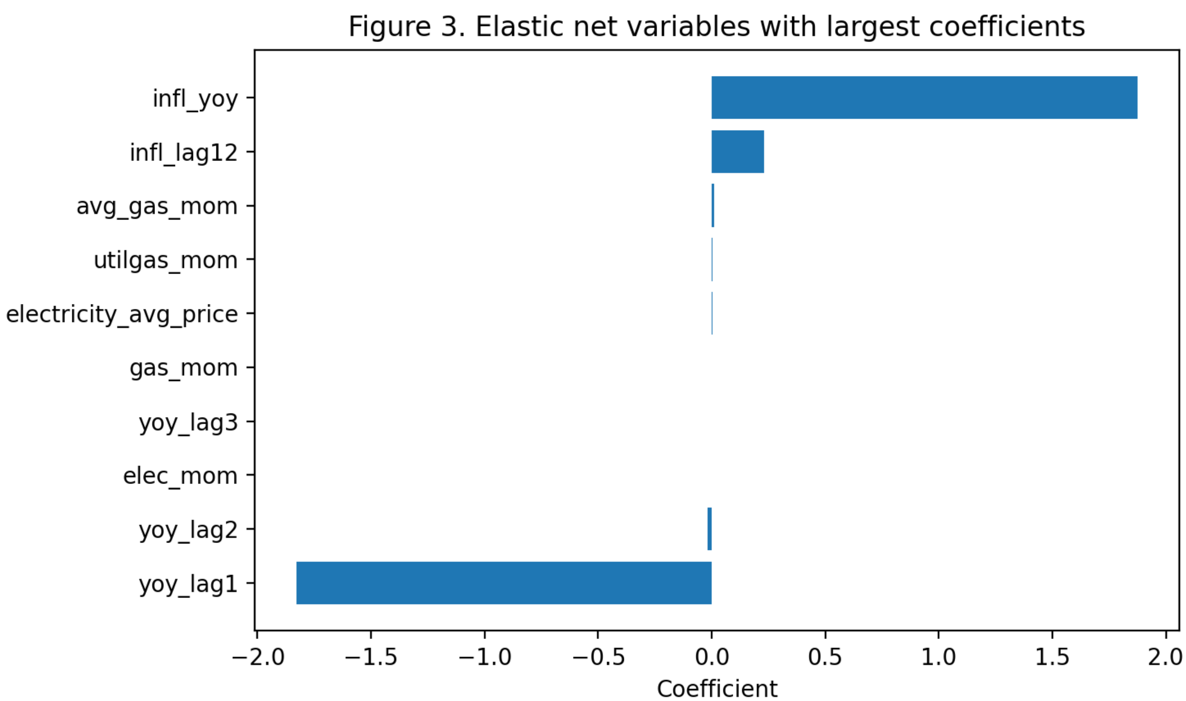

Figure 3. Largest elastic-net coefficients in absolute importance terms.

5. Conclusion

This paper developed a U.S.-focused framework for real-time nowcasting and short-horizon forecasting of inflation using predictive analytics, artificial intelligence, and machine-learning methods applied to high-frequency retail price and energy-market data. Drawing on official pre-2025 public data from the BLS and EIA, the study showed how daily and weekly energy indicators can be transformed into economically meaningful mixed-frequency features and combined with lagged CPI dynamics in a transparent forecasting architecture. The empirical illustration indicates that machine-learning models can outperform naïve and autoregressive benchmarks in this setting, with elastic net performing especially well because it balances flexibility, shrinkage, and interpretability. The findings support a practical conclusion: high-frequency energy and retail signals are most valuable when inflation is changing direction and when conventional lag-only models react too slowly. More broadly, the study argues for a governed hybrid system in which public data pipelines, benchmark econometrics, machine-learning challengers, and expert interpretation operate together. Such a system can improve inflation surveillance for policymakers, financial institutions, and corporate decision makers without displacing official statistics or economic judgment. The evidence therefore supports continued investment in explainable, mixed-frequency inflation-monitoring systems. It is both analytically useful and institutionally feasible. for modern institutions. in practice today.

6. Limitations and Future Directions

Several limitations should qualify the interpretation of this paper. First, the empirical exercise is pseudo-real-time rather than fully vintage-real-time. The predictors are public and timely, but the study does not reconstruct every historical forecast date using archival release calendars and vintage snapshots. Second, the public-data architecture is intentionally compact. It omits proprietary scanner data, web-scraped category prices, card spending flows, rent microdata, wage indicators, and survey expectations that may further improve performance. Third, the focus is mainly on headline CPI, where energy pass-through is especially visible; a separate dedicated framework would be needed for core inflation and for category-level nowcasting. Fourth, the train-test design uses a relatively small monthly sample, which limits how aggressively nonlinear models can be tuned. Fifth, forecast gains observed during 2023-2024 may not generalize uniformly across all macro regimes.

Future research should therefore proceed in five directions. The first is true real-time replication using vintage datasets and forecast-date aligned publication calendars. The second is richer high-frequency data integration, especially scanner, online, and geospatial price systems. The third is disaggregated modeling that nowcasts CPI subcomponents first and then re-aggregates them using expenditure weights. The fourth is probabilistic forecasting, including interval nowcasts and density forecasts that communicate uncertainty more clearly. The fifth is stronger governance research on explainability, drift monitoring, and decision integration for AI-driven macro forecasting systems. Advancing along those lines would move inflation nowcasting from a promising public-data prototype toward a more comprehensive and institutionally robust real-time forecasting platform. Better real-time archives and richer micro price data would be especially valuable. Future work should also compare public-data and proprietary-data architectures under identical evaluation windows. Additional work on cross-country transferability would also be useful. More work on forecast combination across model families is also warranted.

References

[1]. Adil Shah, A., Kabir, S., Razib, M. N. H., & Khan, S. A. (2024). Grid-integrated EV charging systems: Impacts on U.S. power grid stability and resilience. International Journal of Artificial Intelligence Engineering and Transformation, 5(1), 40-45. https://doi.org/10.54660/IJAIET.2024.5.1.40-45

[2]. Aparicio, D., & Bertolotto, M. I. (2020). Forecasting inflation with online prices. International Journal of Forecasting, 36(2), 232-247.

[3]. Araujo, G. S., & Gaglianone, W. P. (2023). Machine learning methods for inflation forecasting in Brazil: New contenders versus classical models. Latin American Journal of Central Banking, 4(2), 100084.

[4]. Arman, M., & Fahim, A. S. M. (2023). AI revolutionizes inventory management at retail giants: Examining Walmart's U.S. operations. Journal of Business and Management Studies, 5(6), 145-148. https://doi.org/10.32996/jbms.2023.5.6.15

[5]. Arman, M., Hasan, M. N., & Rasel, I. H. (2024). Clean energy transition in USA: Big data analytics for renewable energy forecasting and carbon reduction. Journal of Management World, 2024(3), 192-206. https://doi.org/10.53935/jomw.v2024i4.1196

[6]. Arman, M., Rasel, I. H., Razib, M. N. H., & Fahim, A. S. M. (2024). Big data and machine learning for sustainable waste reduction. Journal of Posthumanism, 4(2), 448-467. https://doi.org/10.63332/joph.v4i2.3361

[7]. Atkeson, A., & Ohanian, L. E. (2001). Are Phillips curves useful for forecasting inflation? Federal Reserve Bank of Minneapolis Quarterly Review, 25(1), 2-11.

[8]. Banbura, M., & Modugno, M. (2014). Maximum likelihood estimation of factor models on datasets with arbitrary pattern of missing data. Journal of Applied Econometrics, 29(1), 133-160.

[9]. Bentley, A., Chipeniuk, K., & Krsinich, F. (2024). Online price data, high frequency inflation measures, and formulation of monetary policy in New Zealand. Ottawa Group Working Paper.

[10]. Cavallo, A. (2013). Online and official price indexes: Measuring Argentina's inflation. Journal of Monetary Economics, 60(2), 152-165.

[11]. Cavallo, A., & Rigobon, R. (2016). The billion prices project: Using online prices for measurement and research. Journal of Economic Perspectives, 30(2), 151-178.

[12]. Fahim, A. S. M., Ibrahim, M., Pritty, A. A., & Tania, T. A. (2023). Algorithmic accountability in U.S. consumer FinTech: Governance mechanisms for credit risk, fair lending, and financial stability. Journal of Economics, Finance and Accounting Studies, 5(4), 80-93. https://doi.org/10.32996/jefas.2023.5.4.8

[13]. Fahim, A. S. M., Pritty, A. A., Ibrahim, M., & Tania, T. A. (2024). Real-time payments and real-time fraud: A U.S. FinTech risk framework for RTP rails and consumer protection. Journal of Economics, Finance and Accounting Studies, 6(6), 134-149. https://doi.org/10.32996/jefas.2024.6.6.11

[14]. Fahim, A. S. M., Pritty, A. A., Ibrahim, M., & Tania, T. A. (2025). Explainable AI for medical debt forecasting: Integrating healthcare and FinTech data for risk prediction. Journal of Management World, 2025(6), 92-103. https://doi.org/10.53935/jomw.v2024i4.1253
[15]. Faust, J., & Wright, J. H. (2013). Forecasting inflation. In G. Elliott & A. Timmermann (Eds.), Handbook of Economic Forecasting (Vol. 2A, pp. 2-56). Elsevier.
[16]. Ghysels, E., Santa-Clara, P., & Valkanov, R. (2004). The MIDAS touch: Mixed data sampling regression models. CIRANO Working Paper.
[17]. Giannone, D., Reichlin, L., & Small, D. (2008). Nowcasting: The real-time informational content of macroeconomic data. Journal of Monetary Economics, 55(4), 665-676.
[18]. Ibrahim, M., Huda Razib, M. N., Jahan, N., & Rahman, M. M. (2022). Climate risk, financial stability, and global capital allocation: A predictive analytics approach to assessing climate-related financial risk in international investment markets. Journal of Business and Management Studies, 4(4), 264-276. https://doi.org/10.32996/jbms.2022.4.4.34
[19]. Ibrahim, M., Mahmud, S., Zadid, M. U., Jahan, N., Rahman, M. M., & Fahim, A. S. M. (2024). AI-driven predictive analytics framework for anti-money laundering risk management and financial infrastructure protection in U.S. banking systems. Journal of Economics, Finance and Accounting Studies, 6(1), 155-166. https://doi.org/10.32996/jefas.2024.6.6.12
[20]. Ibrahim, M., Fahim, A. S. M., Zadid, M. U., & Pritty, A. A. (2025). FinTech for climate resilience: Measuring insurance gaps, mortgage stress, and household credit risk in the United States. Journal of Economics, Finance and Accounting Studies, 7(4), 190-205. https://doi.org/10.32996/jefas.2025.7.4.15
[21]. Mahmud, S., Fahim, A. S. M., Rahman, M. M., Jahan, N., & Ibrahim, M. (2025). Artificial intelligence and predictive machine learning for financial fraud detection, cyber risk management, and infrastructure resilience in the U.S. banking industry. British Journal of Multidisciplinary Studies, 3(1), 58-77. https://doi.org/10.32996/bjmss.2025.4.1.6
[22]. Ibrahim, M., Razib, M. N. H., & Rasel, I. H. (2025). The role of data analytics in enhancing ESG transparency in the corporate sector of Bangladesh. Global Journal of Engineering and Technology Advances, 22(1), 81-93. https://doi.org/10.30574/gjeta.2025.22.1.0245
[23]. Jahan, N., Pritty, A. A., Ibrahim, M., Zadid, M. U., Fahim, A. S. M., & Mahmud, S. (2024). Machine learning-driven early warning analytics for identifying market manipulation, irregular trading activity, and suspicious market signals in U.S. stock markets. Journal of Computer Science and Technology Studies, 6(2), 257-283. https://doi.org/10.32996/jcsts.2024.6.2.26
[24]. Kelly, B. T., & Xiu, D. (2023). Economic forecasting with machine learning: A survey. NBER Working Paper 31502.
[25]. Knotek, E. S., II, & Zaman, S. (2024). Nowcasting inflation. Federal Reserve Bank of Cleveland Working Paper 24-06.
[26]. Liu, Y., Pan, R., & Xu, R. (2024). Mending the crystal ball: Enhanced inflation forecasts with machine learning. IMF Working Paper 2024/206.
[27]. Medeiros, M. C., Vasconcelos, G. F. R., Veiga, Á., & Zilberman, E. (2021). Forecasting inflation in a data-rich environment: The benefits of machine learning methods. Journal of Business & Economic Statistics, 39(1), 98-119.
[28]. Menz, J.-O., & Garnitz, J. (2024). Nowcasting consumer price inflation using high-frequency scanner data and machine learning. ECB Working Paper No. 2930.
[29]. Modugno, M. (2013). Now-casting inflation using high frequency data. International Journal of Forecasting, 29(4), 664-675.
[30]. Pritty, A. A., Ibrahim, M., Fahim, A. S. M., & Zadid, M. U. (2024). Generative AI and U.S. financial reporting integrity: Detecting narrative manipulation, risk disclosure gaming, and fraud signals in 10-K filings. Journal of Economics, Finance and Accounting Studies, 6(4), 113-129. https://doi.org/10.32996/jefas.2024.6.4.11
[31]. Razib, M. N. H., Ibrahim, M., & Rasel, I. H. (2025). Predictive analytics and its role in optimizing sustainable supply chain performance. International Journal of Business Management, 8(01), 12-27. http://doi.org/10.35409/IJBMER.2025.3640
[32]. Rasel, I. H., Ibrahim, M., Pritty, A. A., Fahim, A. S. M., & Jahan, N. (2023). Beyond FICO: Enhancing mortgage default forecasting and inclusive lending via multimodal graph neural networks and urban mobility analytics. Frontiers in Computer Science and Artificial Intelligence, 2(2), 62-81. https://doi.org/10.32996/fcsai.2023.2.2.5
[33]. Schnorrenberger, R., Moura, G. V., & others. (2024). Harnessing machine learning for real-time inflation nowcasting. De Nederlandsche Bank Working Paper No. 806.
[34]. Stock, J. H., & Watson, M. W. (2007). Why has U.S. inflation become harder to forecast? Journal of Money, Credit and Banking, 39(s1), 3-33.
[35]. Stock, J. H., & Watson, M. W. (2008). Phillips curve inflation forecasts. NBER Working Paper 14322.
[36]. U.S. Bureau of Labor Statistics. (2025). Handbook of Methods: Consumer Price Index data sources.
[37]. U.S. Bureau of Labor Statistics. (2023). CPI average price data.
[38]. U.S. Energy Information Administration. (2024). Weekly petroleum status report.
[39]. U.S. Energy Information Administration. (2024). Spot prices for crude oil and petroleum products.
[40]. Assenmacher, K., Carstensen, K., & others. (2021). Communication and inflation expectations under high uncertainty. ECB Working Paper.
[41]. Bańbura, M., Giannone, D., Modugno, M., & Reichlin, L. (2013). Now-casting and the real-time data flow. In Handbook chapters on nowcasting and forecasting.
[42]. Bybee, L., Kelly, B., Manela, A., & Xiu, D. (2024). Narrative asset pricing and machine learning in macro-finance. Journal of Finance.
[43]. Chen, M., Engstrom, E., Greatrex, C., & Grishchenko, O. (2023). Identifying financial crises using machine learning on textual data. International Finance Discussion Papers 1374.
[44]. Doz, C., Giannone, D., & Reichlin, L. (2011). A two-step estimator for large approximate dynamic factor models based on Kalman filtering. Journal of Econometrics, 164(1), 188-205.
[45]. Ferrara, L., Simoni, A., & others. (2019). When are Google data useful to nowcast GDP? An approach via pre-selection and shrinkage. International Journal of Forecasting, 35(4), 1400-1414.
[46]. Rigobon, R., & Cavallo, A. (2014). Using online prices to anticipate official CPI inflation. Canon Institute for Global Studies Working Paper.
[47]. Watson, M. W., & Engle, R. F. (1983). Alternative algorithms for the estimation of dynamic factor, MIMIC and varying coefficient regression models. Journal of Econometrics, 23(3), 385-400.