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AI-Based Forecasting Capability and Perceived Inflation Forecasting Effectiveness in Pakistan: The Roles of High-Frequency Data Integration, Nonlinear Pattern Recognition, and Macroeconomic Volatility

Ammara Azam
Department of Agriculture Policy, Law and Governance Centre, University of Agriculture Faisalabad
ammara.azam@uaf.edu.pk
Zara Hasnain (Corresponding Author)
Department of Sociology, University of Agriculture Faisalabad
zarahasnain18@gmail.com
Ayila Nawaz
Department of English, Bahauddin Zakariya University Multan
ayilanawaz99@gmail.com
Saba Javed
Institution of Agriculture and Resource Economics, University of Agriculture Faisalabad
saba.javed@uaf.edu.pk

ABSTRACT

This study examines whether AI-based forecasting capability improves Perceived Inflation Forecasting Effectiveness and how this effect operates through high-frequency data integration and nonlinear pattern recognition under macroeconomic volatility. Integrating dynamic capabilities theory, information-processing theory, and contingency theory, the study conceptualizes AI forecasting capability as an adaptive analytical capacity that converts heterogeneous, fast-moving signals into policy-relevant predictive knowledge. Survey data were collected from 215 forecasting-relevant professionals in Pakistan, including respondents from universities/research institutes, central banking, commercial banking, macroeconomic analysis units, research departments, and data/statistics functions. The model was tested in R using confirmatory factor analysis, reliability and validity diagnostics, HC3 structural regressions, and 5,000-sample bootstrapping for serial mediation and moderated mediation. AI-based forecasting capability showed a significant total effect on Perceived Inflation Forecasting Effectiveness (β=.516, p<.001). The direct effect became nonsignificant after mediators were included, while high-frequency data integration (β=.370, p<.001) and nonlinear pattern recognition (β=.277, p<.001) remained significant. Conditional indirect effects increased under high macroeconomic volatility, supporting first-stage moderated serial mediation. The study shifts debate from whether AI forecasts better to why, when, and through which forecasting mechanisms AI improves inflation prediction. Institutions should invest in algorithms, real-time data pipelines, nonlinear modeling expertise, volatility-responsive governance, transparency, and model discipline for credible policy decision-making under uncertainty.

Keywords: *Artificial Intelligence Capability; Inflation Forecasting; Pakistan, An Emerging-Market Economy; High-Frequency Data; Nonlinear Pattern Recognition; Moderated Mediation; Macroeconomic Volatility*

1. Introduction

Inflation forecasting is no longer a narrow technical exercise undertaken after macroeconomic data are released; it has become a real-time institutional capability that shapes monetary-policy credibility, fiscal planning, financial-market expectations, and household welfare. Altig et al. (2020) show that macroeconomic uncertainty sharply increases during crises, and Caldara and Iacoviello (2022) demonstrate that geopolitical risk can be transmitted rapidly into macro-financial conditions. This shift is especially salient in Pakistan, an emerging-market economy, where inflationary pressure is often transmitted through exchange-rate pass-through, import-price volatility, food and energy shocks, fiscal dominance, financial-market frictions, and abrupt changes in expectations. Jaravel and O'Connell (2020) and Cavallo (2024) further show that real-time price and consumption data can reveal inflation pressures that fixed official baskets may miss during disruptions. In such settings, the costs of forecasting error are not merely statistical. Under-predicted inflation can delay policy tightening and undermine price stability, whereas over-predicted inflation can lead to unnecessarily restrictive policy, suppressed investment, and credibility losses. The methodological challenge is therefore also an institutional challenge: as Carriero et al. (2022) argue for weekly tail-risk nowcasting, forecasting organizations must build systems that can sense volatile signals early, integrate diverse data streams, and identify nonlinear relationships before they appear in official aggregate statistics.

Recent forecasting research has shown that machine-learning and artificial-intelligence methods can improve macroeconomic prediction when they are used in data-rich settings and evaluated through rigorous out-of-sample protocols. Medeiros et al. (2021) provide benchmark evidence that machine-learning models improve inflation forecasts in data-rich environments, while Naghi et al. (2024) extend this debate by reassessing the conditions under which such gains persist. Emerging-market and country-specific evidence is also growing: Mirza et al. (2024) show that machine learning and external-reserve information can improve inflation prediction in emerging economies, and Huang et al. (2025) demonstrate the usefulness of data-rich machine-learning approaches for China's inflation. Research on macroeconomic forecasting more broadly similarly indicates that the value of machine learning does not derive from algorithmic complexity alone; rather, it arises from the combination of nonlinear representation, disciplined regularization, cross-validation, and the ability to use high-dimensional information without collapsing under multicollinearity or overfitting (Athey & Imbens, 2019; Goulet Coulombe, 2024; Goulet Coulombe et al., 2022; Masini et al., 2023; Petropoulos et al., 2022). The question for emerging-market forecasting institutions is therefore not whether AI is fashionable, but whether AI capability is embedded in the data, analytical, and governance routines that make accurate forecasting possible under instability.

The current study addresses this issue by examining AI-based forecasting capability as a higher-order organizational-analytical capability rather than as a single forecasting algorithm. AI capability refers to the coordinated capacity to use machine-learning models, automated feature extraction, hybrid model architectures, data-engineering routines, and expert oversight to produce timely and accurate inflation forecasts. This definition is consistent with contemporary work on AI capability, which emphasizes the complementarity among data resources, technological infrastructure, human expertise, and organizational routines (Ameen et al., 2024; Borges et al., 2021; Duan et al., 2019; Enholm et al., 2022; Mikalef & Gupta, 2021; Mikalef et al., 2021). In the inflation-forecasting context, such capability should matter because it expands the information set, increases the speed of signal extraction, and supports pattern recognition across heterogeneous macro-financial conditions.

However, the extant literature leaves three important gaps. First, prior forecasting studies often compare algorithmic performance but pay less attention to the organizational mechanisms through which AI capability improves forecast quality. This leaves an explanatory gap between algorithmic superiority and institutional forecasting performance (Borges et al., 2021; Enholm et al., 2022; Kourentzes & Fildes, 2026). Second, the role of high-frequency data integration remains theoretically underdeveloped in emerging-market inflation forecasting. Although online prices, payments data, search intensity, financial-market indicators, textual information, and other real-time signals have been shown to improve nowcasting and short-horizon prediction (Aparicio & Bertolotto, 2020; Barbaglia et al., 2023; Bok et al., 2018; Galbraith & Tkacz, 2018; Jaravel & O'Connell, 2020; Macias et al., 2023; Proietti et al., 2021; Richardson et al., 2021; Zheng et al., 2024), it is unclear whether their value is independent or whether they operate as a mediating capability through which AI forecasting systems become effective. Third, the literature frequently acknowledges volatility but rarely models volatility as a boundary condition that changes the strength of AI-enabled forecasting mechanisms. This omission is consequential because the gains from nonlinear and high-dimensional methods may be largest when the macroeconomy is unstable, structural relationships shift, and conventional linear benchmarks deteriorate (Demetrescu et al., 2022; Goulet Coulombe et al., 2022; Guerron-Quintana & Zhong, 2023).

This study therefore develops and tests a moderated serial mediation model linking AI-based forecasting capability to Perceived Inflation Forecasting Effectiveness through high-frequency data integration and nonlinear pattern recognition, with macroeconomic volatility as a contextual moderator. The model is grounded in three mutually reinforcing theoretical perspectives. Dynamic capabilities theory explains why forecasting institutions need adaptive analytical capabilities to sense, seize, and reconfigure information resources under volatility (Mikalef et al., 2019; Vial, 2019; Warner & Wager, 2019). Information-processing theory explains why richer, faster, and more heterogeneous data streams reduce uncertainty only when organizations have sufficient processing capacity (Bok et al., 2018; Richardson et al., 2021). Contingency theory explains why the value of AI-based forecasting capability is not uniform but depends on the volatility of the macroeconomic environment (Altig et al., 2020; Guerron-Quintana & Zhong, 2023).

Empirically, the study uses survey evidence from 215 professionals involved in macroeconomic analysis, inflation forecasting, research, data science, central banking, commercial banking, and academic research. The empirical model tests six hypotheses: the direct effect of AI-based forecasting capability on Perceived Inflation Forecasting Effectiveness; the mediating role of high-frequency data integration; the mediating role of nonlinear pattern recognition; the serial

pathway from high-frequency data integration to nonlinear pattern recognition; the moderating effect of macroeconomic volatility; and the moderated mediation mechanism by which volatility strengthens the indirect AI-accuracy pathway. The analysis was conducted in R using confirmatory factor analysis, reliability and validity diagnostics, heteroskedasticity-consistent structural estimation, and bootstrapped conditional indirect effects, an approach consistent with current recommendations for conditional process models and survey-method rigor (Hayes & Rockwood, 2020; Jordan & Troth, 2020; Podsakoff et al., 2024).
The study contributes in three ways. First, it reframes AI in macroeconomic forecasting from an algorithm-comparison issue to a capability-building issue, thereby connecting forecasting research with contemporary theories of AI capability and dynamic capabilities (Ameen et al., 2024; Mikalef & Gupta, 2021; Vial, 2019). Second, it identifies high-frequency data integration and nonlinear pattern recognition as two distinct but sequential mechanisms that explain how AI capability improves Perceived Inflation Forecasting Effectiveness, extending work on nowcasting, online prices, and mixed-frequency learning (Aparicio & Bertolotto, 2020; Babii et al., 2022; Barbaglia et al., 2023; Macias et al., 2023). Third, it shows that macroeconomic volatility strengthens the indirect effects of AI capability, suggesting that AI forecasting capability is particularly valuable when Pakistan, an emerging-market economy face instability, data lags, and nonlinear price dynamics (Goulet Coulombe et al., 2022; Guerron-Quintana & Zhong, 2023; Mirza et al., 2024). The following section develops the theoretical foundation for these claims before deriving the hypotheses and presenting the empirical model.

2. Theoretical Support

The study is anchored in a multi-theoretical framework because AI-based inflation forecasting is simultaneously a technological, informational, and contextual phenomenon. A single theory would be insufficient to explain why AI capability matters, how its effect is transmitted through data and pattern-recognition mechanisms, and why its value may vary across volatility conditions. Theoretical integration is particularly important in emerging-market settings, where forecasting performance depends not only on model sophistication but also on the institutional ability to process incomplete, noisy, and rapidly changing information (Kourentzes & Fildes, 2026; Mikalef et al., 2019; Petropoulos et al., 2022).
Dynamic capabilities theory provides the broadest explanatory foundation. Contemporary digital-transformation research conceptualizes AI capability as a dynamic capability because it enables organizations to sense environmental changes, seize opportunities from data, and reconfigure analytical routines when conditions shift (Ameen et al., 2024; Mikalef et al., 2018; Mikalef & Gupta, 2021; Mikalef et al., 2021; Vial, 2019; Warner & Wager, 2019). In the present study, AI-based forecasting capability is not treated as ownership of software or isolated technical expertise. It is defined as an institutionally embedded ability to combine machine-learning algorithms, high-quality data assets, computational infrastructure, expert validation, and feedback learning into an adaptive forecasting system. This perspective is essential because inflation forecasting in Pakistan, an emerging-market economy requires continuous adaptation to new shocks rather than mechanical application of a fixed model.

Dynamic capabilities theory informs the independent variable and the interpretation of the main relationship. If AI-based forecasting capability is a dynamic analytical capability, then forecasting institutions with stronger AI capability should be better able to identify early price signals, update model structures, and generate more accurate predictions than institutions relying exclusively on static econometric routines. This logic is consistent with empirical evidence showing that machine-learning models can be useful in macroeconomic forecasting when they exploit large information sets and identify nonlinearities that conventional models miss (Goulet Coulombe, 2024; Goulet Coulombe et al., 2022; Medeiros et al., 2021; Naghi et al., 2024). It also fits emerging-market evidence indicating that machine-learning methods can improve inflation prediction when they incorporate relevant macro-financial predictors, such as exchange-rate and reserve variables (Huang et al., 2025; Mirza et al., 2024).

Information-processing theory explains the first mediating mechanism: high-frequency data integration. Forecasting institutions confront uncertainty because inflation-relevant information is dispersed across official statistics, financial markets, commodity prices, online prices, exchange-rate movements, payments systems, surveys, and expectations indicators. Information-processing theory suggests that performance improves when an organization's information-processing capacity matches the uncertainty and equivocality of its environment. In inflation forecasting, high-frequency data integration increases the timeliness and granularity of the information set. Online prices can reveal price adjustments before official CPI releases (Aparicio & Bertolotto, 2020; Macias et al., 2023), payments and transaction data can improve real-time macroeconomic inference (Galbraith & Tkacz, 2018; Jaravel & O'Connell, 2020), and mixed-frequency nowcasting and machine-learning approaches can incorporate monthly, weekly, daily, and real-time indicators into short-horizon forecasts (Babii et al., 2022; Bok et al., 2018; Proietti et al., 2021; Richardson et al., 2021). AI capability should therefore improve forecasting accuracy partly because it allows organizations to transform fast-moving heterogeneous data into usable predictive inputs.

Information-processing theory also supports the second mediating mechanism: nonlinear pattern recognition. High-frequency data become useful only when the forecasting system can extract meaningful structure from them. Inflation dynamics are often nonlinear because price changes depend on thresholds, regime shifts, asymmetric pass-through, supply-chain disruptions, policy credibility, and interaction effects across exchange rates, commodity prices, fiscal conditions, and expectations. Machine-learning methods are valuable in such environments because they can approximate nonlinear functions, detect interactions, and model changing relationships without imposing overly restrictive linear specifications (Athey & Imbens, 2019; Chernozhukov et al., 2018; Goulet Coulombe, 2024; Goulet Coulombe et al., 2022; Hauzenberger et al., 2023; Huber et al., 2023; Masini et al., 2023). Nonlinear pattern recognition is therefore conceptualized as the analytical capability through which an institution identifies complex inflation signals, detects regime-dependent patterns, and translates high-frequency information into forecast-relevant knowledge.

Contingency theory explains macroeconomic volatility as a boundary condition. The value of AI capability should not be assumed to be constant across all conditions. Under low volatility, conventional models may perform reasonably well because relationships among predictors and inflation are more stable. Under high volatility, however, forecasting systems must process more signals, detect sharper nonlinearities, and update assumptions more rapidly. Recent macroeconomic forecasting research shows that crises and uncertainty episodes challenge standard forecasting models and can alter the relative value of alternative methods (Altig et al., 2020; Demetrescu et al., 2022; Guerron-Quintana & Zhong, 2023). Goulet Coulombe et al. (2022) further show that machine-learning gains are associated with uncertainty, financial stress, and nonlinear macro-financial conditions. Contingency theory therefore suggests that macroeconomic volatility should strengthen the informational and pattern-recognition pathways through which AI capability improves inflation forecast accuracy.

Together, these theories map directly onto the conceptual model. Dynamic capabilities theory explains why AI-based forecasting capability should be positively associated with forecasting accuracy. Information-processing theory explains why high-frequency data integration and nonlinear pattern recognition mediate this relationship. Contingency theory explains why macroeconomic volatility moderates the effect of AI capability and its indirect pathways. This theoretical triangulation avoids a purely technological interpretation of AI and instead positions AI-enabled inflation forecasting as an adaptive institutional process, consistent with recent calls to consider people, processes, and governance in central-bank forecasting (Kourentzes & Fildes, 2026; Petropoulos et al., 2022). The model therefore examines not only whether AI capability matters, but how and when it becomes consequential for emerging-market inflation forecasting.

3. Hypothesis Development

AI-based forecasting capability should improve Perceived Inflation Forecasting Effectiveness because it enhances the ability of forecasting institutions to process larger information sets, identify complex relationships, and update predictions as conditions evolve. Traditional inflation forecasting models remain useful for benchmark comparison and theoretical interpretation, but they often struggle when inflation is driven by nonlinear pass-through, abrupt supply shocks, changing policy credibility, and heterogeneous expectations. AI-based methods can address these difficulties by using ensemble learning, regularization, automated feature selection, and nonlinear functional forms to exploit high-dimensional macro-financial data (Babii et al., 2022; Chernozhukov et al., 2018; Masini et al., 2023). Empirical research on inflation forecasting shows that machine-learning models can outperform standard benchmarks in data-rich environments (Medeiros et al., 2021; Naghi et al., 2024), and emerging-market evidence suggests that machine-learning approaches can improve forecast accuracy when they incorporate relevant external and macro-financial indicators (Huang et al., 2025; Mirza et al., 2024). From a dynamic capabilities perspective, AI capability enables forecasting institutions to sense and respond to inflation signals more effectively. Therefore:

H1. AI-based forecasting capability has a positive effect on Perceived Inflation Forecasting Effectiveness in Pakistan, an emerging-market economy.

High-frequency data integration is expected to mediate the relationship between AI-based forecasting capability and Perceived Inflation Forecasting Effectiveness. AI capability increases the institution's ability to ingest and harmonize heterogeneous data, including online prices, commodity prices, exchange rates, financial-market indicators, payments data, textual signals, and other short-cycle indicators. The forecasting value of such data is increasingly documented in studies showing that online prices and real-time indicators can improve inflation nowcasting and short-term forecasting (Aparicio & Bertolotto, 2020; Barbaglia et al., 2023; Bok et al., 2018; Galbraith & Tkacz, 2018; Macias et al., 2023; Zheng et al., 2024). However, high-frequency signals are often noisy, unbalanced, and subject to missingness, seasonality, and structural breaks. AI capability becomes valuable because it provides routines for automated cleaning, feature extraction, mixed-frequency alignment, and model updating. Once integrated, these data streams should improve Perceived Inflation Forecasting Effectiveness by reducing information delays and increasing the sensitivity of the forecasting system to emerging price pressures. Thus:

H2. High-frequency data integration mediates the relationship between AI-based forecasting capability and Perceived Inflation Forecasting Effectiveness.

Nonlinear pattern recognition is also expected to mediate the relationship between AI-based forecasting capability and Perceived Inflation Forecasting Effectiveness. Inflation processes in Pakistan, an emerging-market economy are rarely linear or stable. Exchange-rate depreciation may have small effects during stable periods but large effects when expectations become unanchored. Food and energy shocks may propagate asymmetrically across sectors. Policy signals may affect expectations differently depending on credibility and market stress. AI-based forecasting capability allows institutions to model these nonlinearities through methods such as random forests, gradient boosting, neural networks, support-vector machines, and hybrid ensembles. Goulet Coulombe et al. (2022) identify nonlinearity as a central source of machine-learning gains in macroeconomic forecasting, while Hauzenberger et al. (2023), Huber et al. (2023), and Medeiros et al. (2021) show that nonlinear and flexible models can improve inflation and macroeconomic forecasts by exploiting complex predictor structures. Therefore, AI capability should enhance nonlinear pattern recognition, which in turn should improve forecast accuracy. Hence:

H3. Nonlinear pattern recognition mediates the relationship between AI-based forecasting capability and Perceived Inflation Forecasting Effectiveness.

The mediation process is also expected to be serial. AI capability first expands the relevant information environment by integrating high-frequency data. Yet richer data alone do not guarantee accuracy; they must be transformed into meaningful predictive patterns. High-frequency data integration should therefore precede and enable nonlinear pattern recognition. This sequence is theoretically consistent with information-processing theory: organizations first acquire and integrate signals, then interpret them through analytical routines. It is also consistent with forecasting practice, where online prices, real-time indicators, textual signals, and mixed-frequency data become useful only after they are converted into features, interactions, regime indicators, or nonlinear predictors (Babii et al., 2022; Barbaglia et al., 2023; Huber et al., 2023; Proietti et al., 2021; Richardson et al., 2021; Zheng et al., 2024). Thus, AI capability is expected to improve Perceived Inflation Forecasting Effectiveness through a sequential pathway from high-frequency data integration to nonlinear pattern recognition. Therefore:

H4. AI-based forecasting capability improves Perceived Inflation Forecasting Effectiveness through a serial pathway from high-frequency data integration to nonlinear pattern recognition.

Macroeconomic volatility is expected to moderate the relationship between AI-based forecasting capability and Perceived Inflation Forecasting Effectiveness. In stable environments, simple models and historical averages may already capture much of the predictable component of inflation. In volatile environments, however, forecasting institutions face greater uncertainty, more frequent structural shifts, and stronger nonlinear interactions among prices, exchange rates, commodities, financial variables, and expectations. Under such conditions, AI capability should become more valuable because it enables faster updating, broader signal extraction, and greater flexibility. This expectation is supported by evidence that forecasting during crises requires models capable of adapting to abnormal observations and shifting relationships (Altig et al., 2020; Barbaglia et al., 2023; Guerron-Quintana & Zhong, 2023), and that machine-learning gains are related to uncertainty, financial stress, and time-varying volatility (Demetrescu et al., 2022; Goulet Coulombe et al., 2022). Therefore:

H5. Macroeconomic volatility moderates the relationship between AI-based forecasting capability and Perceived Inflation Forecasting Effectiveness, such that the positive effect of AI-based forecasting capability is stronger under higher macroeconomic volatility.

Finally, macroeconomic volatility is expected to moderate the indirect pathways from AI capability to forecasting accuracy. Volatility should increase the need for high-frequency data because official statistics arrive too slowly to capture rapidly changing inflationary pressure. It should also increase the value of nonlinear pattern recognition because relationships among inflation drivers become less stable and more asymmetric. The effect is expected to be particularly strong in the serial pathway: under volatility, AI capability should be more likely to strengthen high-frequency data integration, which then supports nonlinear pattern recognition and improves forecasting accuracy. This moderated mediation logic directly combines dynamic capabilities, information-processing, and contingency arguments, while aligning with crisis-forecasting evidence that data timeliness, model flexibility, and institutional processes become more important when the macroeconomy is unstable (Carriero et al., 2022; Kourentzes & Fildes, 2026; Petropoulos et al., 2022). Therefore:

H6. Macroeconomic volatility moderates the indirect effect of AI-based forecasting capability on Perceived Inflation Forecasting Effectiveness through high-frequency data integration and nonlinear pattern recognition, such that the indirect effect is stronger at higher levels of macroeconomic volatility.

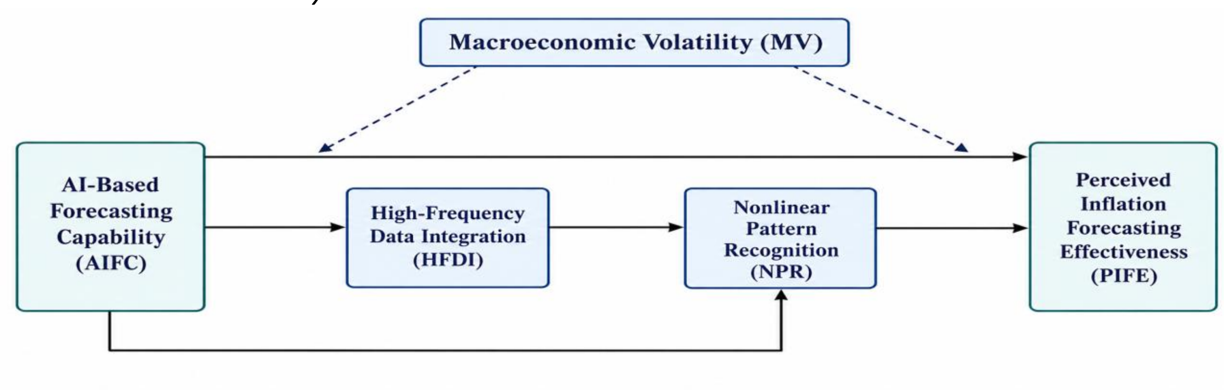

Figure 1. Conceptual framework

4. Methodology

The study adopted a quantitative explanatory research design to test a theoretically specified moderated serial mediation model. The design is appropriate because the objective was not to compare forecasting algorithms directly but to examine whether AI-based forecasting capability is associated with Perceived Inflation Forecasting Effectiveness and whether this association operates through data-integration and pattern-recognition mechanisms under macroeconomic volatility. Moderated mediation is appropriate when theory specifies that the strength of an indirect mechanism depends on a contextual condition (Hayes & Rockwood, 2020). The unit of analysis was the professional forecasting judgment of respondents with experience or functional proximity to macroeconomic analysis, inflation forecasting, data science, research, and financial-sector forecasting.

The empirical context of this study is Pakistan, an emerging economy characterized by inflation volatility, exchange-rate pressure, fiscal constraints, food and energy price shocks, and high sensitivity to external macro-financial disturbances. Pakistan provides a theoretically appropriate setting for examining AI-based inflation forecasting capability because forecasting institutions operate under uncertainty, data delays, nonlinear price dynamics, and volatile macroeconomic conditions.

A purposive expert-sampling strategy was used because the constructs require domain-specific knowledge. Respondents were eligible if they were affiliated with organizations or functions relevant to macroeconomic analysis, financial forecasting, economic research, central banking, commercial banking, data/statistics, or academic/research institutions. Data were collected through a structured questionnaire. The final sample comprised 215 respondents. To ensure contextual consistency, respondents were screened for functional relevance to inflation forecasting, macroeconomic analysis, statistics, financial-sector forecasting, within the Pakistani institutional context; therefore, the final analytical sample was treated as Pakistan-based.

Analytical Strategy

Data were analysed in R through a sequential procedure. First, data screening was conducted to examine missing values, out-of-range responses, multivariate outliers, and straight-line response patterns. Second, measurement quality was assessed using Cronbach's alpha, composite reliability, average variance extracted, standardized factor loadings, HTMT ratios, the Kaiser–Meyer–Olkin statistic, and Bartlett's test of sphericity. Confirmatory factor analysis was then used to test the proposed five-factor measurement model and compare it with a one-factor model. Common method bias was examined using Harman's single-factor variance and CFA model comparison, while recognizing that single-factor diagnostics alone are insufficient (Baumgartner & Weijters, 2021; Howard et al., 2024; Jordan & Troth, 2020; Podsakoff et al., 2024). Third, structural relationships were estimated using standardized coefficients with HC3 heteroskedasticity-consistent standard errors. Finally, mediation, serial mediation, conditional indirect effects, and moderated mediation were tested using 5,000 bootstrap samples, as bootstrapping provides robust confidence intervals for indirect effects (Hayes & Rockwood, 2020). Control variables included total professional experience, inflation/macroeconomic forecasting experience, and AI/ML forecasting familiarity.

Measures

All constructs were measured using multi-item reflective scales adapted from prior literature and contextualized for AI-based inflation forecasting in Pakistan. Responses were captured on a seven-point Likert scale ranging from 1 = strongly disagree to 7 = strongly agree. AI-based forecasting capability (AIFC) was measured with seven items assessing institutional use of AI/ML models, technological infrastructure, forecasting-team expertise, model integration, continuous retraining, comparison with traditional forecasts, and automated data-driven forecasting capability, consistent with AI capability and digital analytics research (Mikalef & Gupta, 2021; Mikalef et al., 2021; Enholm et al., 2022). High-frequency data integration (HFDI) was measured with seven items capturing the use of real-time macro-financial indicators, alternative digital data sources, online prices, transaction data, data harmonization, and integration of official and non-traditional data sources, following research on nowcasting, online prices, payments data, and high-frequency macroeconomic information (Aparicio & Bertolotto, 2020; Bok et al., 2018; Galbraith & Tkacz, 2018; Macias et al., 2023). Nonlinear pattern recognition (NPR) was measured with six items assessing the ability of AI models to identify hidden patterns, nonlinear relationships, interaction effects, structural breaks, regime shifts, and unusual inflationary signals during shocks, in line with machine-learning and nonlinear macroeconomic forecasting literature (Athey & Imbens, 2019; Goulet Coulombe et al., 2022; Hauzenberger et al., 2023). Macroeconomic volatility (MV) was measured with five items reflecting exchange-rate instability, commodity-price shocks, unpredictable macroeconomic conditions, policy uncertainty, and external shocks, consistent with studies on uncertainty, geopolitical risk, and crisis-related macroeconomic volatility (Altig et al., 2020; Caldara & Iacoviello, 2022; Guerron-Quintana & Zhong, 2023). Perceived Inflation Forecasting Effectiveness (PIFE) was measured with six items capturing perceived reductions in forecast errors, improved short- and medium-term forecast accuracy, detection of inflation turning points, reliability during shocks, and timeliness compared with traditional forecasting approaches, consistent with prior research on machine learning, forecast evaluation, and forecasting accuracy in macroeconomic contexts (Medeiros et al., 2021; Naghi et al., 2024; Petropoulos et al., 2022).

5. Results

The sample and data-screening results in table 1. indicate that the dataset was suitable for measurement and structural analysis. No missing values or out-of-range Likert responses were detected. Multivariate outlier analysis identified no cases exceeding the Mahalanobis criterion at $p < .001$; the threshold was 20.515 and the maximum observed distance was 17.479. Country/economic context: Pakistan-based respondents: 215; 100% of the final analytical sample. Twenty-three cases were flagged for straight-line response patterns in at least one construct. These flags were treated as quality indicators requiring review rather than automatic deletion because indiscriminate exclusion can bias expert-sample data, particularly when some constructs may legitimately receive consistent responses.

Table 1. Sample Profile and Data Screening Summary

Panel	Variable / diagnostic	Key categories or result
Demographic profile	Institution type	University/research institute: 42 (19.5%); central bank: 35 (16.3%); commercial bank: 35 (16.3%)

	Professional role	Economist: 44 (20.5%); researcher: 41 (19.1%); data scientist: 38 (17.7%)
	Department/function	Macroeconomic analysis: 50 (23.3%); statistics/data: 42 (19.5%); research: 37 (17.2%)
	Academic qualification	Master: 83 (38.6%); MPhil/MS: 56 (26.0%); PhD: 47 (21.9%)
	Professional experience	6-10 years: 70 (32.6%); 3-5 years: 48 (22.3%); 11-15 years: 43 (20.0%)
	Forecasting experience	4-7 years: 59 (27.4%); 1-3 years: 56 (26.0%); 8-10 years: 29 (13.5%); missing: 14 (6.5%)
	AI/ML familiarity	Moderate: 68 (31.6%); low: 60 (27.9%); high: 53 (24.7%); expert: 34 (15.8%)
	Study Area	100% Pakistan
Data screening	Missing values	0
	Out-of-range Likert values	0
	Multivariate outliers	0 cases at Mahalanobis p < .001; threshold = 20.515; maximum distance = 17.479
	Straight-line flags	23 cases flagged in at least one construct; reviewed as quality indicators rather than automatic exclusions

Table 2 reports descriptive statistics, reliability, convergent validity, and correlations. Cronbach's alpha values ranged from .893 for macroeconomic volatility to .933 for nonlinear pattern recognition, exceeding conventional reliability expectations. Composite reliability values ranged from .894 to .933, indicating internal consistency. Average variance extracted values ranged from .628 to .700, supporting convergent validity. The square roots of AVE ranged from .793 to .837 and were consistent with the reported correlation structure. Correlations among constructs were positive and theoretically coherent. AI-based forecasting capability correlated with high-frequency data integration ($r = .63$, $p < .001$), nonlinear pattern recognition ($r = .60$, $p < .001$), macroeconomic volatility ($r = .32$, $p < .001$), and Perceived Inflation Forecasting Effectiveness ($r = .59$, $p < .001$). HFDI was strongly correlated with PIFE ($r = .73$, $p < .001$), and NPR was also strongly correlated with PIFE ($r = .70$, $p < .001$), providing preliminary support for the proposed mediating mechanisms.

Table 2. Descriptive Statistics, Reliability, Convergent Validity, and Correlation Matrix

Construct	M	SD	Alpha	CR	AVE	Key correlations
AIFC	4.537	1.291	.929	.929	.652	HFDI .63***; NPR .60***; MV .32***; PIFE .59***
HFDI	4.193	1.343	.928	.928	.648	NPR .72***; MV .37***; PIFE .73***
NPR	4.411	1.383	.933	.933	.700	MV .39***; PIFE .70***
MV	3.961	1.356	.893	.894	.628	PIFE .47***
PIFE	4.622	1.348	.922	.922	.664	-

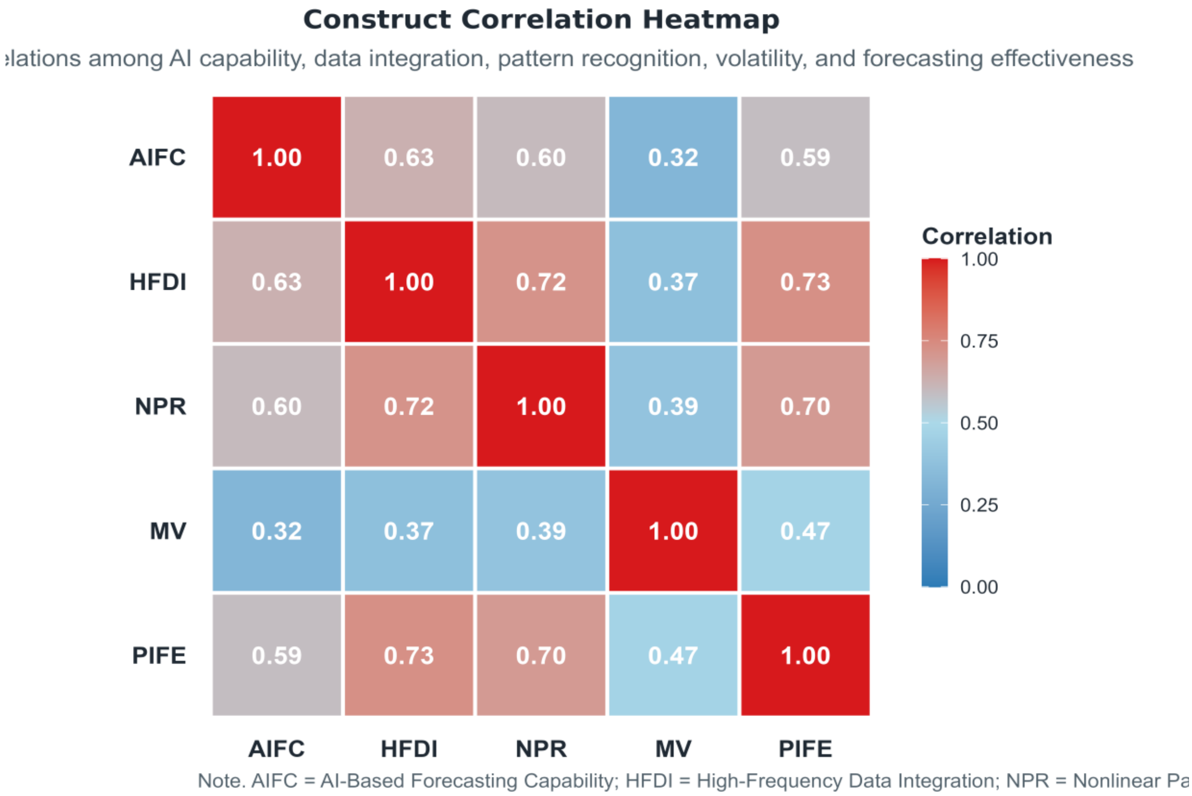

Figure 2. Construct correlation heatmap of the study variables.

The heatmap presents the correlation structure among AI-Based Forecasting Capability (AIFC), High-Frequency Data Integration (HFDI), Nonlinear Pattern Recognition (NPR), Macroeconomic Volatility (MV), and Perceived Inflation Forecasting Effectiveness (PIFE). Darker red cells indicate stronger positive correlations, whereas lighter blue cells indicate weaker positive correlations. The strongest associations appear between HFDI and PIFE, HFDI and NPR, and NPR and PIFE, supporting the proposed data-integration and pattern-recognition mechanisms in the conceptual model.

Table 3. shows the confirmatory factor analysis supported the five-factor measurement model. Model fit was strong: $\chi^2(424) = 525.518$, $p = .001$; CFI = .980; TLI = .978; RMSEA = .033; SRMR = .043. These indices exceed recommended cutoffs for applied social-science research. The one-factor comparison model fit poorly: $\chi^2(434) = 1979.494$, $p < .001$; CFI = .695; TLI = .674; RMSEA = .129; SRMR = .106. This comparison supports the distinctiveness of the five constructs and reduces concern that a single general response factor explains the data. Factorability was also strong, with KMO = .956 and Bartlett's $\chi^2(465) = 5248.024$, $p < .001$. Harman's single-factor variance was 47.690%, below the 50% heuristic; however, following recent warnings about overreliance on Harman's test (Howard et al., 2024; Podsakoff et al., 2024), the result is interpreted alongside CFA comparison, reliability, convergent validity, and discriminant evidence rather than as a standalone proof against common method bias.

Table 3. Measurement Model, Factorability, Common Method Bias, and Multicollinearity Diagnostics

Diagnostic	Statistic/model	Result	Interpretation
CFA fit	Five-factor measurement model	chi-square (424)=525.518, p=.001; CFI=.980; TLI=.978; RMSEA=.033; SRMR=.043	Strong fit
CFA comparison	One-factor model	chi-square (434)=1979.494, p<.001; CFI=.695; TLI=.674; RMSEA=.129; SRMR=.106	Substantially poorer
Factorability	KMO	.956	Excellent
Factorability	Bartlett's test	chi-square(465)=5248.024, p<.001	Significant
Common method bias	Harman single-factor variance	47.690%	Below 50% heuristic
Loadings	Standardized loading ranges	AIFC .744-.869; HFDI .782-.842; NPR .783-.875; MV .693-.848; PIFE .775-.850	Convergent validity supported
Multicollinearity	Structural VIF	AIFC 3.038; HFDI 2.475; NPR 2.295; MV 1.234; AIFC x MV 1.107	No problematic multicollinearity

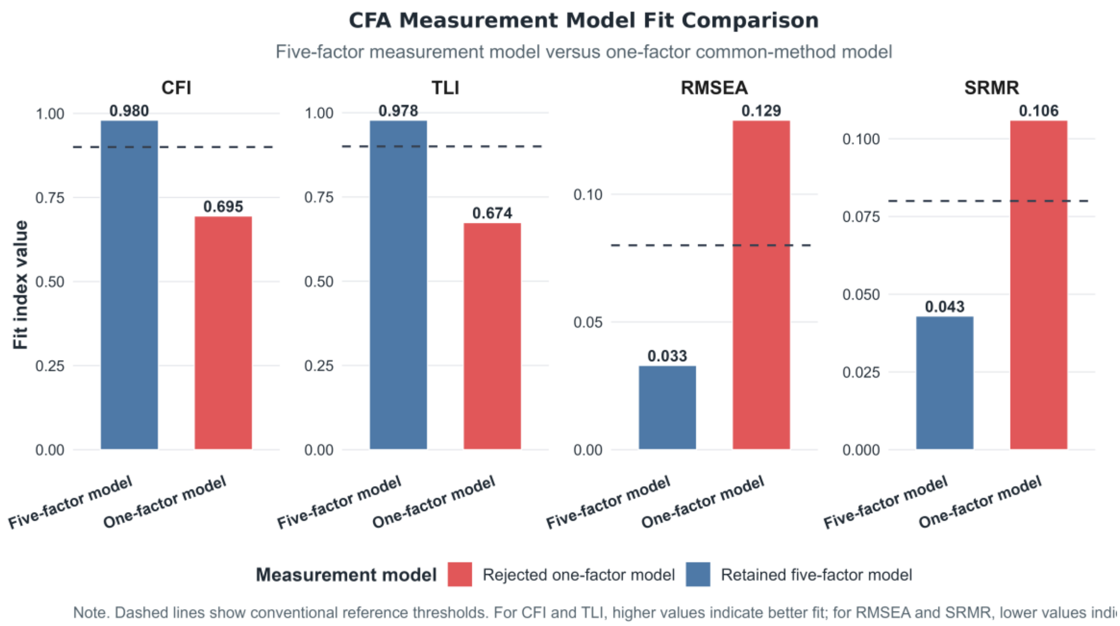

Figure 3. CFA measurement model fit comparison.

The figure compares the retained five-factor measurement model with the rejected one-factor common-method model across four key fit indices: CFI, TLI, RMSEA, and SRMR. The five-factor model demonstrates substantially superior fit, with high incremental fit indices (CFI = .980; TLI = .978) and low absolute/residual fit indices (RMSEA = .033; SRMR = .043). In contrast, the one-factor model shows poor fit across all criteria, supporting the discriminant validity of the five *latent constructs and reducing concern that the observed relationships are driven by a single common-method factor.*

Table 4. shows the Structural estimates provide a nuanced pattern of support. H1 was supported in the total-effect model: AI-based forecasting capability had a significant positive effect on Perceived Inflation Forecasting Effectiveness (β = .516, SE = .087, t = 5.907, $p < .001$, 95% CI [.345, .687]), explaining 35.3% of variance. In the mediator model predicting HFDI, AIFC was significant (β = .515, SE = .085, $p < .001$), macroeconomic volatility was significant (β = .192, SE = .053, $p < .001$), and the AIFC × MV interaction was significant (β = .139, SE = .047, p = .003), with $R^2 = .463$. In the mediator model predicting NPR, AIFC (β = .237, p = .005), HFDI (β = .524, $p < .001$), and MV (β = .123, p = .019) were significant, with $R^2 = .563$. In the final model predicting PIFE, HFDI (β = .370, $p < .001$), NPR (β = .277, $p < .001$), and MV (β = .188, $p < .001$) were significant, while the direct effect of AIFC was reduced and became nonsignificant (β = .118, p = .099). This attenuation indicates that the effect of AI capability operates largely through the proposed mediating mechanisms rather than through a residual direct pathway.

Table 4. Structural Model Results and Explained Variance

Hypothesis/model	Dependent variable	Predictor	beta	SE	t	p	95% CI	R2
H1	PIFE	AIFC	.516	.087	5.907	<.001	[.345, .687]	.353
M1	HFDI	AIFC	.515	.085	6.064	<.001	[.348, .681]	.463
M1	HFDI	MV	.192	.053	3.628	<.001	[.088, .295]	
M1/H6	HFDI	AIFC x MV	.139	.047	2.960	.003	[.047, .232]	
M2	NPR	AIFC	.237	.084	2.812	.005	[.072, .402]	.563
M2	NPR	HFDI	.524	.064	8.252	<.001	[.400, .649]	
M2	NPR	MV	.123	.053	2.344	.019	[.020, .227]	
Final	PIFE	AIFC	.118	.072	1.648	.099	[-.022, .259]	.637
Final	PIFE	HFDI	.370	.060	6.130	<.001	[.252, .488]	
Final	PIFE	NPR	.277	.060	4.607	<.001	[.159, .395]	
Final	PIFE	MV	.188	.044	4.313	<.001	[.103, .273]	
H5	PIFE	AIFC x MV	.069	.042	1.633	.103	[-.014, .151]	

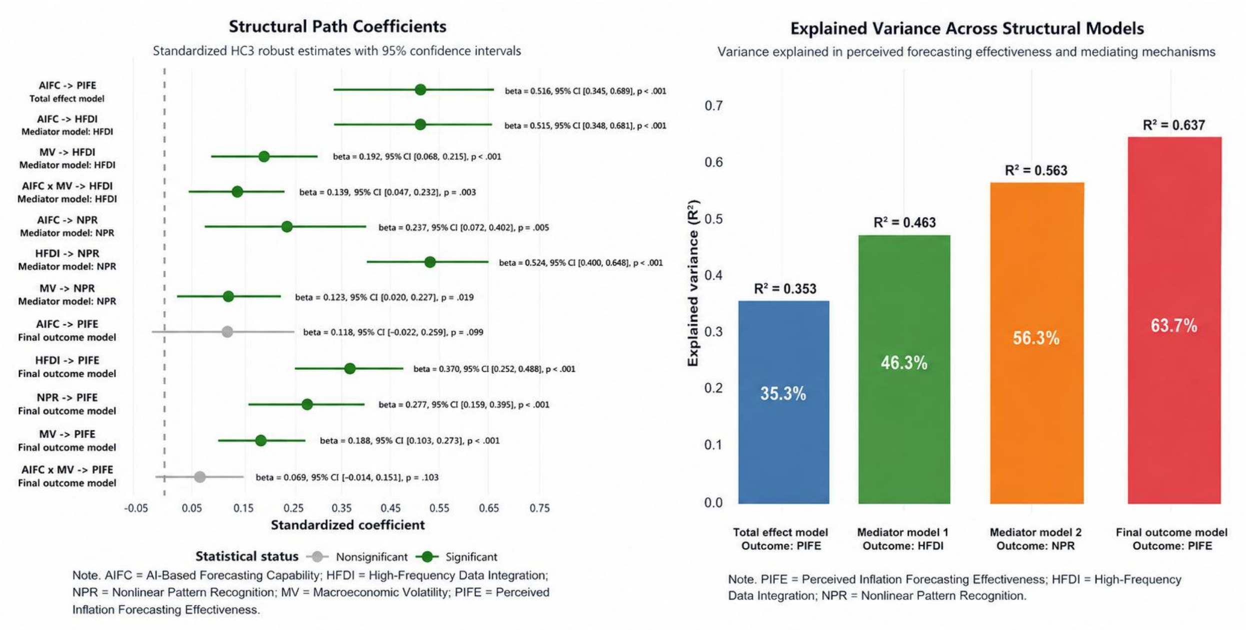

Figure 4. Structural path coefficients and explained variance across structural models.

Panel A presents standardized HC3 robust structural path coefficients with 95% confidence intervals, distinguishing statistically significant and nonsignificant effects. Panel B reports the explained variance (R^2) across the total-effect, mediator, and final outcome models. The results show that the final structural model explains the largest proportion of variance in Perceived Inflation Forecasting Effectiveness, while High-Frequency Data Integration and Nonlinear Pattern Recognition account for substantial variance in the proposed mediating mechanisms.

Table 5. shows the moderation hypothesis received partial but not full support. The AIFC × MV interaction on PIFE was positive but not statistically significant in the final model (β = .069, SE = .042, t = 1.633, p = .103, 95% CI [-.014, .151]). However, simple slopes showed that the conditional association between AIFC and PIFE was significant only at high macroeconomic volatility (β = .187, SE = .081, t = 2.308, p = .022, 95% CI [.028, .346]) and nonsignificant at mean and low volatility. Therefore, H5 should be interpreted cautiously: volatility appears to condition the practical relevance of AI capability, but the formal interaction term on the direct PIFE path did not meet the conventional significance threshold.

The mediation and moderated mediation results were stronger. The conditional indirect effect of AIFC on PIFE through HFDI increased from .138 at low MV to .190 at mean MV and .241 at high MV, with all confidence intervals excluding zero. The indirect effect through NPR was significant (.066, 95% CI [.019, .124]). The serial indirect effect through HFDI and NPR was significant at low MV (.055, 95% CI [.023, .098]), mean MV (.075, 95% CI [.036, .128]), and high MV (.096, 95% CI [.045, .163]). The first-stage moderated mediation index through HFDI was .051, 95% CI [.016, .094], and the first-stage moderated serial mediation index was .020, 95% CI [.005, .041]. These findings support H2, H3, H4, and H6. Substantively, the results indicate that AI-based forecasting capability improves forecasting accuracy primarily by strengthening high-frequency data integration and nonlinear pattern recognition, and that the mediated pathway becomes stronger when macroeconomic volatility is higher.

Table 5. Bootstrapped Conditional Indirect Effects, Moderated Mediation, and Simple Slopes

Panel	Effect	MV level/index	Estimate	SE/statistic	95% CI

Conditional direct	AIFC -> PIFE	Low MV	.046	-	[-.123, .207]
	AIFC -> PIFE	Mean MV	.117	-	[-.023, .257]
	AIFC -> PIFE	High MV	.188	-	[.028, .345]
Conditional indirect	AIFC -> HFDI -> PIFE	Low MV	.138	-	[.071, .224]
	AIFC -> HFDI -> PIFE	Mean MV	.190	-	[.114, .282]
	AIFC -> HFDI -> PIFE	High MV	.241	-	[.144, .358]
	AIFC -> NPR -> PIFE	All MV levels	.066	-	[.019, .124]
	AIFC -> HFDI -> NPR -> PIFE	Low MV	.055	-	[.023, .098]
	AIFC -> HFDI -> NPR -> PIFE	Mean MV	.075	-	[.036, .128]
	AIFC -> HFDI -> NPR -> PIFE	High MV	.096	-	[.045, .163]
Moderated mediation	First-stage via HFDI	Index	.051	-	[.016, .094]
	First-stage serial mediation	Index	.020	-	[.005, .041]
Simple slopes	AIFC -> PIFE	Low MV (-1 SD)	.050	SE=.085; t=.582; p=.561	[-.118, .217]
	AIFC -> PIFE	Mean MV	.118	SE=.072; t=1.648; p=.101	[-.022, .259]
	AIFC -> PIFE	High MV (+1 SD)	.187	SE=.081; t=2.308; p=.022	[.028, .346]

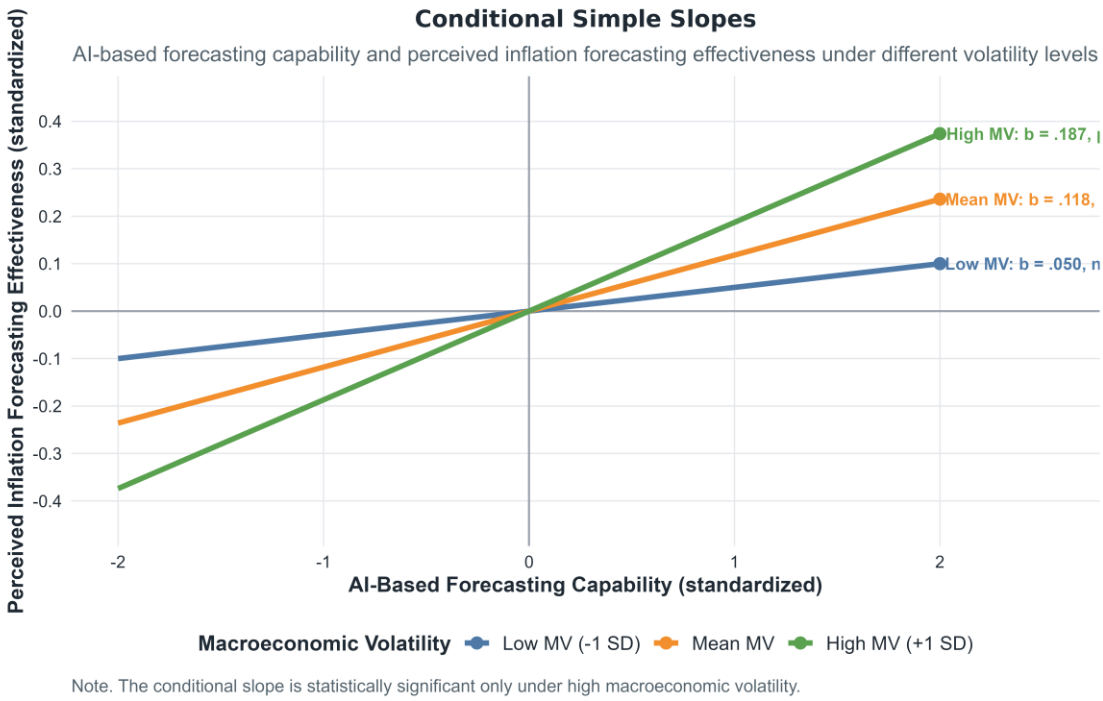

Figure 5. Conditional simple slopes of AI-based forecasting capability on Perceived Inflation Forecasting Effectiveness across levels of macroeconomic volatility.

The figure illustrates the conditional relationship between AI-Based Forecasting Capability (AIFC) and Perceived Inflation Forecasting Effectiveness (PIFE) at low, mean, and high levels of Macroeconomic Volatility (MV). The slope is strongest under high macroeconomic volatility, indicating that AI-based forecasting capability becomes more consequential for forecasting effectiveness when the macroeconomic environment is unstable. The conditional effect is statistically significant at high MV but not at low or mean MV, suggesting that volatility strengthens the practical relevance of AI-enabled forecasting capability.

6. Discussion

The findings advance the inflation-forecasting literature by showing that AI-based forecasting capability matters most when it is embedded in specific data and analytical mechanisms. The significant total effect of AIFC on PIFE is consistent with prior evidence that machine-learning approaches can improve inflation forecasts in data-rich settings (Medeiros et al., 2021; Naghi et al., 2024) and emerging-market contexts (Huang et al., 2025; Mirza et al., 2024). However, the nonsignificant residual direct effect in the final model is theoretically more revealing than a simple direct-effect interpretation. It suggests that AI capability does not automatically produce accurate inflation forecasts merely because an institution uses advanced algorithms. Rather, AI capability improves accuracy when it helps institutions integrate high-frequency data and transform that information into nonlinear predictive insight, a mechanism-oriented interpretation consistent with AI capability research (Ameen et al., 2024; Enholm et al., 2022; Mikalef & Gupta, 2021).

The mediating role of HFDI confirms the importance of timely and granular data. Emerging-market inflation can change before official statistics capture the underlying dynamics. Online prices, commodity indicators, exchange rates, financial-market variables, payments data, and communication signals may provide early warning information, but only if forecasting institutions can integrate them into coherent modeling pipelines. The positive effect of HFDI on PIFE aligns with research showing that online prices and massive high-frequency datasets can improve nowcasting and inflation forecasting (Aparicio & Bertolotto, 2020; Galbraith & Tkacz, 2018; Jaravel & O'Connell, 2020; Macias et al., 2023). The study extends that literature by showing that high-frequency data integration is not merely a technical input; it is a mediating organizational capability that explains why AI-based forecasting capability improves perceived forecasting accuracy.

The mediating role of NPR is equally important. The results show that nonlinear pattern recognition remains a significant predictor of PIFE after controlling for AIFC, HFDI, MV, and controls. This supports the argument that the forecasting value of AI lies partly in its ability to detect complex inflation relationships that may be invisible to linear models. The finding aligns closely with Goulet Coulombe et al. (2022), who argue that nonlinearity is a key channel through which machine learning improves macroeconomic forecasting, and with recent evidence on nonlinear dimension reduction and nonparametric mixed-frequency forecasting (Hauzenberger et al., 2023; Huber et al., 2023). It also extends this claim to an emerging-market inflation context and shows that nonlinear pattern recognition can be modeled as a distinct capability rather than inferred from algorithmic performance alone.

The serial mediation finding clarifies the sequence through which AI capability becomes useful. AI capability first strengthens high-frequency data integration; integrated data then supports nonlinear pattern recognition; and nonlinear pattern recognition improves forecasting accuracy. This sequence is theoretically plausible and empirically supported. It means that institutions cannot obtain the full benefits of AI by investing only in modeling software. They must also invest in data governance, data pipelines, interoperability, and analytical routines that convert heterogeneous signals into model-ready information, consistent with dynamic capability and data-analytics capability research (Mikalef et al., 2018; Mikalef et al., 2019; Warner & Wager, 2019). Without HFDI, nonlinear models may lack timely inputs; without NPR, high-frequency data may add noise rather than insight.

The role of macroeconomic volatility adds important nuance. The direct interaction between AIFC and MV on PIFE was not statistically significant at the conventional threshold, so the direct moderation hypothesis should not be overstated. Yet the significant first-stage interaction and moderated mediation indices reveal that volatility strengthens the indirect mechanism. This pattern is theoretically meaningful: volatility may not simply make AI directly more predictive; instead, it increases the value of the data-integration and serial interpretation processes that AI capability enables. In volatile environments, high-frequency data become more important because official data are delayed and conventional relationships may deteriorate. Nonlinear pattern recognition becomes more important because inflation drivers interact in asymmetric and regime-dependent ways, which is consistent with crisis-forecasting evidence and work on uncertainty-related machine-learning gains (Altig et al., 2020; Demetrescu et al., 2022; Goulet Coulombe et al., 2022; Guerron-Quintana & Zhong, 2023). Thus, volatility amplifies the mechanism rather than only the direct association.

The study confirms, extends, and qualifies prior literature. It confirms the general claim that AI and machine learning can improve macroeconomic forecasting when properly designed (Goulet Coulombe, 2024; Goulet Coulombe et al., 2022; Medeiros et al., 2021; Petropoulos et al., 2022). It extends the literature by identifying HFDI and NPR as capability-based mediators in emerging-market inflation forecasting. It qualifies technologically deterministic claims by showing that AI capability is not sufficient on its own; its value depends on complementary data infrastructure, analytical interpretation, and volatility-responsive routines. This interpretation is aligned with dynamic capabilities theory, which treats technology as valuable only when combined with reconfigurable organizational capabilities (Mikalef et al., 2019; Vial, 2019), and with information-processing theory, which emphasizes the match between uncertainty and processing capacity.

7. Theoretical Implications

The study offers four theoretical implications. First, it advances AI capability theory by translating the concept into a macroeconomic forecasting context. Much AI capability research has focused on firm performance, creativity, agility, marketing outcomes, and business value. This study shows that AI capability is also relevant for public-policy and macro-financial forecasting institutions. The theoretical contribution is not simply domain extension; it shows that AI capability can be understood as an institutional forecasting capability that integrates data, models, expertise, and feedback learning.

Second, the study contributes to forecasting theory by moving beyond algorithm comparisons. Forecasting research often asks which model performs best against a benchmark. This study asks why an AI-enabled forecasting system may be more accurate. By identifying HFDI and NPR as mediating mechanisms, it provides an explanatory architecture that connects forecasting inputs, analytical processing, and accuracy outcomes. This helps bridge the gap between statistical forecasting research and organizational theories of capability, while complementing recent claims that forecasting performance also depends on organizational processes and expert judgment.

Third, the study refines information-processing theory in the context of high-frequency macroeconomic data. It shows that increased data availability is useful only when forecasting institutions have the capacity to integrate and interpret it. This is important because the contemporary data environment can create both informational richness and informational overload. The results suggest that AI capability reduces uncertainty not by passively accumulating data but by organizing high-frequency signals into nonlinear predictive structures, consistent with evidence on online prices, mixed-frequency nowcasting, payments data, and textual macroeconomic forecasting.

Fourth, the study contributes to contingency theory by showing that macroeconomic volatility conditions the indirect value of AI capability. The strongest evidence appears in the moderated mediation paths rather than the direct interaction. This implies that environmental volatility may operate by intensifying the importance of intermediate capabilities rather than by uniformly increasing the direct technology-performance relationship. Theoretically, this helps explain why AI may produce inconsistent direct effects across contexts: its impact depends on whether volatility activates the data-integration and pattern-recognition mechanisms through which AI capability becomes valuable.

8. Practical and Policy Implications

The results have direct implications for central banks, finance ministries, commercial banks, forecasting units, research institutes, and international organizations working in Pakistan, an emerging-market economy. First, investment in AI forecasting should not be limited to model acquisition. Institutions should build end-to-end forecasting pipelines that include data ingestion, cleaning, frequency alignment, metadata documentation, model validation, and human expert review. AI software without high-frequency data integration is unlikely to produce sustained accuracy gains, a point consistent with research on AI business value and digital transformation capabilities.

Second, central banks and statistical agencies should strengthen access to alternative and high-frequency data sources. Online prices, payments data, financial-market indicators, commodity prices, exchange-rate data, and expectations measures can provide early signals of inflation pressure. However, the use of these data requires clear governance rules concerning privacy, representativeness, revision policies, data licensing, and continuity. Forecasting institutions should create data-quality protocols so that high-frequency signals improve forecasts rather than introduce instability, as demonstrated by the practical forecasting value and limitations of online prices, consumption baskets, payments data, and nowcasting indicators.

Third, institutions should develop nonlinear modeling expertise. The results suggest that nonlinear pattern recognition is a distinct predictor of Perceived Inflation Forecasting Effectiveness. Forecasting teams should therefore include economists, statisticians, data engineers, and machine-learning specialists who can jointly evaluate model performance, interpret nonlinear results, and prevent overfitting. Model governance should include benchmark comparisons, rolling-window validation, stability checks, and transparent documentation of model updates, consistent with best-practice forecasting guidance and machine-learning cautions in economics.

Fourth, policymakers should treat macroeconomic volatility as a trigger for enhanced forecasting routines. During periods of currency instability, commodity-price shocks, fiscal stress, or financial-market turbulence, forecasting institutions should increase update frequency, expand data monitoring, and use models capable of detecting nonlinear pass-through and regime shifts. The results indicate that AI capability is particularly valuable when volatility strengthens the need for real-time data integration, which is consistent with evidence on crisis nowcasting, uncertainty, geopolitical risk, and macroeconomic forecasting under abnormal conditions.

Fifth, forecasting communication should distinguish between algorithmic confidence and institutional confidence. AI forecasts may improve accuracy, but policy credibility depends on whether decision-makers understand the forecast drivers and limitations. Institutions should combine AI-generated forecasts with interpretable diagnostics, scenario analysis, and expert narrative. This is especially important in Pakistan, an emerging-market economy where public trust and expectations management are central to inflation control, and it aligns with the recent argument that central-bank forecasting quality depends on people and processes as well as numerical models.

9. Limitations and Future Research

The study has limitations that should be interpreted constructively. First, the cross-sectional design limits causal inference. Although the hypotheses are theoretically grounded and the mediation model is statistically supported, longitudinal or experimental designs would provide stronger evidence of temporal ordering. Future research should track forecasting institutions over time to examine whether improvements in AI capability precede measurable improvements in forecast accuracy. Methodologically, future designs could also draw on panel, causal-machine-learning, and structural-parameter approaches to strengthen causal interpretation.

Second, the dependent variable is based on professional perceptions of forecasting accuracy rather than archival forecast errors such as RMSE, MAE, or directional accuracy. Professional assessments are valuable because they capture institutional experience and decision usefulness, but future studies should combine survey measures with objective forecast-performance data. This would allow researchers to test whether perceived accuracy corresponds to realized improvements in official forecasting exercises and to compare the capability model against established forecast-evaluation practices,

First, although this study is explicitly situated in Pakistan and the respondent screening process targeted forecasting-relevant professionals working in Pakistan-based institutional and research contexts, the single-country design limits the cross-national generalizability of the findings. Pakistan provides a theoretically appropriate emerging-market setting because inflation forecasting is shaped by exchange-rate pressure, food and energy price shocks, fiscal constraints, external vulnerability, and macroeconomic volatility. However, the mechanisms identified in this study may operate differently in economies with stronger data infrastructures, more stable monetary-policy regimes, lower inflation volatility, or more mature AI-based forecasting systems. Future research should therefore replicate the model across multiple emerging and advanced economies to examine whether the relationships among AI-based forecasting capability, high-frequency data integration, nonlinear pattern recognition, macroeconomic volatility, and inflation forecasting effectiveness are context-specific or generalizable across institutional environments.

Although the study is situated in Pakistan, the sample does not allow comparison across multiple emerging economies. Future research should replicate the model across other emerging markets to test whether the proposed AI–forecasting capability mechanism varies by monetary-policy regime, institutional quality, inflation history, and data infrastructure.

10. Conclusion

This study developed and tested a moderated serial mediation model explaining how AI-based forecasting capability improves Perceived Inflation Forecasting Effectiveness in Pakistan, an emerging-market economy. The findings show that AI capability has a significant total effect on forecasting accuracy, but this effect operates primarily through high-frequency data integration and nonlinear pattern recognition. The serial pathway is especially important: AI capability expands and organizes high-frequency information, which enables forecasting institutions to identify nonlinear inflation patterns and produce more accurate forecasts. Macroeconomic volatility strengthens the indirect mechanism, indicating that AI capability is most valuable when forecasting environments are unstable and conventional models are under pressure. The central scholarly contribution is therefore a shift from algorithmic comparison to capability explanation. AI does not improve inflation forecasting simply because it is technologically advanced. It improves forecasting when institutions build the data, analytical, and governance capabilities required to transform volatile signals into predictive knowledge. For Pakistan, an emerging-market economy, where inflation forecasting is complicated by data delays, external shocks, and nonlinear pass-through, this capability-based view offers a stronger foundation for both theory and policy. The future of inflation forecasting will depend not only on better models, but on better institutions capable of learning from fast-moving data under uncertainty.

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