International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 14, Issue 11, CONFLUENCE - 2026

Artificial Intelligence and Monetary Policy: A Review of Inflation and Policy Transmission

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Abstract - As Artificial Intelligence (AI), data-driven technologies and intelligent systems for monetary-policy decision-making rapidly surface, new possibilities are emerging in economic analysis and policy decision-making. This paper is a review that conceptually explores the connection between Artificial Intelligence (AI) and monetary policy with a special emphasis on the problems of inflation and monetary-policy transmission. The paper draws on theoretical and interdisciplinary literature to examine how Artificial Intelligence (AI) can impact central banks notion of the inflation process, their analysis of economic data, inflation expectations, and monetary policy transmission. It also considers the changing nature of data, predictive technologies, and computational tools in policy analysis and does not see Artificial Intelligence as a substitute for the economic theory or institutional judgement. The vital role of Artificial Intelligence on analyzing inflation expectations, policy communication, monetary policy responsiveness and the impact of the monetary tightening in different channels is discussed. Finally, the paper provides some conceptual reflections and considerations on possible problems of embedding Artificial Intelligence (AI) in monetary-policy frameworks, such as the transparency, explainability of the Artificial Intelligence (AI) tools, dependency on data and responsible use of Artificial Intelligence (AI). What makes this review noteworthy is that it connects emerging Artificial Intelligence (AI) perception with existing monetary policy frameworks especially regarding inflation and the way policy is transmitted, and looks at what this means for data-driven analysis, inflation expectations, policy communication and the responsible use of AI in central banking with a specific emphasis on emerging economies.

Keywords: Artificial Intelligence, Monetary Policy, Inflation, Policy Transmission, Inflation Expectations

INTRODUCTION

Monetary policy has always depended on information that is incomplete, delayed, noisy and subject to revision. Central banks must infer the current state of an economy from indicators such as prices, output, wages, credit, financial conditions and expectations, while simultaneously judging how those variables may respond to policy. The modern monetary-policy framework therefore combines theory, econometric models, surveys, market information and institutional judgement. The rapid expansion of artificial intelligence (AI) changes this information environment by making it increasingly feasible to process large, high-frequency and unstructured datasets alongside conventional macroeconomic statistics (Doerr et al., 2021; Varian, 2014). The relevance of AI to monetary policy is consequently broader than the use of a new forecasting algorithm. Central banks are exploring machine learning, natural-language processing, web-scraped prices, alternative data and generative AI for statistics, macroeconomic analysis, supervision and related functions (Araujo et al., 2024). The Bank for International Settlements (BIS) similarly emphasizes that AI can help central banks extract information from unstructured data, improve nowcasting and strengthen policy analysis, while also introducing new forms of model, data, cyber and concentration risk (Bank for International Settlements [BIS], 2024). The central question of this review is how can machine learning integrate with traditional economics, specifically in the context of policy frameworks, without threatening the foundations of those frameworks? These distinctions are important because machine learning is predominantly focused on prediction and other areas of economics are primarily focused on structural, counterfactual and behavioral economics (Athey & Imbens, 2017; Mullainathan & Spiess, 2017). A model may predict inflation with a very high degree of accuracy, but may not provide insight into what the policy impact would be under a different monetary policy regime. The focus of this review is on the conceptual frameworks and literature is organized based on four main questions. First, how does AI change the way central banks observe and model inflation? Second, how can AI contribute to the measurement of inflation expectations and the interpretation of policy communication? Third, how might AI-assisted analysis interact with established channels of monetary-policy transmission? Fourth, what institutional risks arise when data-driven systems are embedded in policy

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ISSN: 2278-0181
Vol. 14, Issue 11, CONFLUENCE - 2026

processes, particularly in emerging economies? The discussion is thematic rather than empirical and synthesizes monetary theory, econometric research, central-bank publications and recent evidence on AI applications.

CONCEPTUAL FOUNDATIONS: MONETARY POLICY, INFLATION AND THE AI INFORMATION LAYER

Monetary policy remains theory-led

There is a long history in economic theory that shows the interaction between inflation and monetary policy. The expectations-augmented Phillips curve showed that inflation cannot be understood independently of expected inflation. Friedman (1968) and Phelps (1967) demonstrated the role of expectations with the limits of systematic monetary policy and inflation. Subsequently, expectations and nominal rigidities were integrated with the interest rate and became the principal elements of New Keynesian monetary policy (Clarida et al., 1999). So far, the primary integration of AI within this field has been for information and computational purposes. AI is well positioned to process and interpret the large amounts of data that exist and complement formal theories and improve the pace with which policymakers are able to absorb information (Araujo et al., 2024). The main obstacle is more a measurement problem than a theory problem, thus the relationship between theory and enhanced measurement is more appropriate than theory and AI. The addition of measurement can open up new and heretofore inaccessible, costly and time-consuming areas of analysis.

Prediction versus explanation

This distinction is critical to interpreting the expanding body of research on machine learning and economics. Varian (2014) showed how, in the presence of many potential predictors and with non-linear relationships, flexible algorithms become very useful. Mullainathan and Spiess (2017) underscored that machine learning solves a different prediction problem from the usual parameter-estimation problems in econometrics. Athey and Imbens (2017) demonstrated the importance of considering the key steps in the policy process when bridging prediction to action such as identification and Causal structure. Regarding monetary policy, a very successful AI forecast should be considered as an informative input, rather than a complete policy rule. This is analogous to the Lucas Critique (Lucas, 1976). Relationships among policies estimated within a particular behavioral or policy regime may not be policy invariant. If expectations change and a break from the status quo is actually part of policy (as is the case with the implementation of new monetary policies), historic regularity may not hold and AI systems may become less reliable, precisely when policy decisions are the most consequential. Therefore, the combined consideration of AI, economics and other disciplines may help fill gaps in knowledge.

ARTIFICIAL INTELLIGENCE AND THE ANALYSIS OF INFLATION

Inflation forecasting and nowcasting

AI has the potential to dramatically change the forecasting of inflation. As Medeiros et al. (2021) found, in a data rich environment, predicting inflation with ML is possible with large sets of predictors and non-linear relationships that may be difficult to represent in traditional economic models. They find that for U.S. inflation, ML-based models outperform benchmarks with random forests achieving the best results. It is unlikely that one method has been established as the best, but rather that the presence of nonlinear structures within inflation allow ML to excel. The same logic extends to nowcasting. Traditional macroeconomic indicators are often released with delays while prices, transactions, financial-market data and other information can arrive at much higher frequency. BIS work identifies nowcasting as a prominent central-bank application of AI and BIS work also illustrates the broader effort to combine novel high-frequency data with advanced analytical techniques (Araujo et al., 2024; BIS, 2024). Such tools may be especially valuable during turning points, when official statistics provide an incomplete picture of the economy's current state. Evidence from India is increasingly consistent with this direction. The Reserve Bank of India (RBI) has reported the use of AI/ML to analyze corporate sentiment from media sources, experimental machine-learning approaches to CPI inflation forecasting and AI/ML models that combine unstructured information with traditional data for selected food-price components (Reserve Bank of India [RBI], 2025).

Nonlinearity, structural change and the inflation process

Inflation processes are state dependent. The same shock may produce different outcomes when supply constraints, labor-market conditions, expectations or financial conditions change. Flexible AI models are potentially useful because they can approximate interactions and nonlinearities without imposing the same functional form as a linear model. BIS research likewise finds that machine-learning models can improve the prediction of inflation drivers and that expectations are among the most informative predictors considered in the analysis (Kohlscheen, 2021). Yet flexibility creates a trade-off. A model that adapts easily to the historical data may also learn temporary correlations, regime-specific relationships or noise. This is especially problematic around

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rare events because the data used to train a model contain relatively few observations of extreme states. Flexibility alone is not the issue but as it pertains to stress testing, central banks must develop models that structural shift and alternative regime stress test. Out of sample, the methods must withstand systematic risk to be valid. AI plays an important role as a value add when it integrates into economic framework and signals value that structural shift may not.

Inflation expectations and the measurement of beliefs

Inflation expectations are a particularly important bridge between AI and monetary theory because expectations connect information with present behaviour. Coibion and Gorodnichenko (2015) document evidence of information rigidities and state dependence in expectations formation, while Coibion et al. (2018) argue for greater use of survey information in macroeconomic analysis. These findings make real-time measurement of beliefs valuable because the public may not process information continuously or in the same way as professional forecasters or financial markets. AI and natural-language processing can expand the set of observable indicators. Angelico et al. (2022) used Italian social-media text and machine-learning techniques to construct daily measures of consumer inflation expectations and found meaningful relationships with survey and market-based measures. Recent research also shows that the content and tone of central-bank communication can be quantified with domain-specific language models and related to inflation expectations and future policy information (Byun et al., 2026). These applications provide an example of the shift from reliance on classic representational surveys to the more frequent capturing of expectational information from other sources. Digital traces are not the same as representational information. Expectations stated and debated in the online world are self-selected, amplified and may reflect attitude, emotion, and political disagreement rather than an expectation about inflation. Thus, the belief statement may not represent a distribution of the population regarding the expectation about inflation. Hence, AI creates an opportunity for broader measurement of expectations, but it is still the responsibility of analysts to assess the representativeness of the sample and the economic meaning of the information.

AI AND MONETARY-POLICY TRANSMISSION

The traditional transmission architecture

Channels through which monetary policy acts on the economy differ in importance. Traditionally, the interest rate channel has been the most prominent of these (Mishkin, 1996). The implications of the credit channel have been more recently explored. Bernanke and Gertler (1995) argue that in addition to the balance-sheet channel, monetary policy can influence the economy through the bank-lending channel. This can occur via inter-bank market frictions and informational asymmetries. Expectations, in particular forward-looking expectations, are key in the determination of longer-term interest rates, asset prices, and spending and inflation. Machine learning and natural language processing can help better interpret and leverage unstructured financial data. Central banks can use more disaggregated transactional data to better understand how firms and households respond to changing monetary policy. Further, by combining AI with central bank data, agencies can more effectively discern nonlinear responses to monetary policy changes.

Credit, financial intermediation and heterogeneous pass-through

The application of technology to the financial services industry is modifying the pricing and evaluation of credit risk. For credit evaluation, for example, the use of artificial intelligence (AI) and machine learning can lead to a structure and processing of information that can be substantially different from traditional credit risk assessment systems. This can in turn, transform credit extension and change the manner in which interest rate risk is transmitted to borrowers. At the same time, different and possibly more credit intermediaries supported by technology can alter the financial system's sensitivity to different policies. The Bank for International Settlements (BIS) research, for example, indicates that AI can be a disruptive technology that alters financial intermediation and therefore, complicate the relationship between the central bank's policy rate and the financial system conditions (BIS, 2024). If lending and financial intermediation depend more on algorithms and less on human judgment, the financial system's response to monetary policy can be more rapid and larger. Ultimately, a central bank can face a situation where its ability to analyze the financial system (and the framework on which the analysis is based) is improved but the system itself is more unpredictable.

Communication as a transmission channel

Incorporating communication into monetary policy is an innovation in many central banks. The justification is that their statements, addresses, forecasts and directions influence prospects and related market prices (Blinder et al., 2008; Woodford, 2005). AI expands both sides of this relationship. On the policy side, natural-language processing can help classify messages, track changes in tone, compare communication across documents and test whether language conveys information consistently. On the receiving side, AI can help measure how market participants, households or media interpret policy announcements. Recent evidence illustrates the

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potential. Byun et al. (2026) use large language models to quantify Federal Open Market Committee statements and press conferences and find that the two forms of communication carry different informational content for market expectations. AI can make a previously difficult-to-measure transmission layer more visible. At the same time using AI to optimize communication could create feedback effects. If market participants know that central-bank language is being algorithmically classified, small wording changes may receive disproportionate attention. The ECB has focused on the risk that the market may come to expect policy changes based primarily on what the central bank communicates, reducing the role of other market signals (Cipollone, 2024). As a result, market signals may begin to echo and amplify the signals communicated by the central bank. As a result, the so-called 'policy puzzle' becomes partially reflexive. Indeed, at a certain point, financial market participants may begin to look for and trade based on signals embedded within the central bank's communication, thus moving away from traditional economic data.

AI as an Economic Shock: When Technology Changes the Object of Monetary Policy

A second relationship between AI and monetary policy should be distinguished from AI as a policy tool. AI is itself a technological shock that can change productivity, investment, labour demand, prices and financial conditions. BIS modelling indicates that AI can raise aggregate productivity and output but that the inflation response depends on the timing of supply and demand effects and on whether households and firms anticipate higher future productivity (Aldasoro et al., 2024). Recent BIS analysis similarly stresses that AI can affect supply and demand simultaneously making cyclical signals harder to interpret (Aldasoro et al., 2026). From a monetary-policy perspective this means that measured disinflation could reflect a supply-side productivity improvement, while stronger investment and income growth could create demand pressure at the same time. AI-driven changes in labour markets can alter wage dynamics, while automated pricing systems can change the frequency with which firms adjust prices. The direction and magnitude of the overall inflation effect are therefore unclear in advance. This focuses on understanding how inflation works, rather than using AI to forecast inflation or figure out policy transmission. With AI, the speed at which prices change also changes. There could be an impact on the lag between when policy becomes more restrictive and when inflation falls. With more investment opportunities, the interest sensitivity of spending could change. Discussions within the European Central Bank and Bank for International Settlements (BIS) indicate the effect of the adoption of AI and other technologies will be more dependent on the financial system and the structure of the markets, rather than on technology (BIS, 2024; Lane, 2026).

Emerging Economies and the Indian Context

The situation regarding AI in developing economies is somewhat different. Developing countries may be able to gain more from AI tools that integrate and process data and improve the timeliness of macroeconomic data. At the same time, they may be faced with challenges of inadequate digital infrastructures and cyber resilience, lack of skills and administrative data and pervasive informal sectors, higher level of economic and financial system's heterogeneity**.** Considering the proposals of this study the challenges of Merging and Emerging Economies are likely to be related to the quality of the data and instruments available. In the absence of reliable and full set of official statistics, AI will not be able to bridge the knowledge gaps in the economy by itself. Considering that context, it may be as necessary to prioritize data infrastructure and metadata as it is to focus on model architecture. Thus, the emphasis the BIS places on data governance and central bank data cooperation as prerequisites for the prudent use of AI is logical (BIS, 2024). In the absence of central bank data cooperation, it is difficult for individual central banks to meet the conditions the BIS outlines to facilitate the safe adoption of AI.

GOVERNANCE, EXPLAINABILITY AND RESPONSIBLE USE

Transparency and explainability

The use of AI by central banks creates unique challenges for their governance. That is because the decisions made by central banks impact the entire economy and are usually made by government agencies. Unlike other fields in which the use of AI has been considered, central banks cannot simply reject a model to use a human alternative. To trust a model for central banking use, decision-makers need to have the opportunity to understand why the model generates one forecast and not another. They also need to determine the factors that influence the model and forecast. Finally, if a factor is beyond the control of the model, decision-makers must consider how to act upon the uncertainty in the model's forecast. Trust in AI is comprised of several factors, including reliability and validity and integrity and privacy. Explainability does not necessarily mean that every model used by central banks must be entirely transparent and clear to the public. Models used to inform central banking policy must provide sufficient level of detail so that economists can evaluate the reasonableness of the model's predictions and determine the policy's vulnerabilities and limitations. Models must also inform how a policy will address a specific issue. An opaquer model may inform and contextualize central banking policy more than a less powerful model.

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Data dependence, bias and model risk

AI systems also reflect the biases and other limitations of the data they are trained on. Historical data can contain measurement errors and breakages, bias and other changes. Digitized data can also create other problems. The people generating the data may not be similar to the population about which monetary policy is concerned. There is also the risk of feedback. If a central bank begins using an AI system to formulate monetary policy, other economic agents may change their behavior, and then the system may no longer be useful. For these reasons, the BIS and central banks have published or presented studies and working papers focusing on data and model integrity and authority (Araujo et al., 2024; BIS, 2024). Reliance on third parties is also arising. For certain, advanced AI systems, a few cloud, model and data providers exist. This may create operational and cyber risks, and concentration risks, which did not exist with traditional statistical systems. Therefore, central banks need to strike a balance of accessing the latest AI systems and protecting their core systems. The same holds true for other central banking systems. This is as true for technology as it is for regulatory and other systems.

The human-institutional dimension

The literature reviewed here leans towards a human-in-the-loop approach to AI-assisted central bank policy. In the article Araujo et al. (2024), AI is framed as assisting central banks with their mandate and is not pictured as replacing central bank staff with AI. Therefore, in this context, AI must be thought of as augmenting central bank staff with additional data, rather than central bank staff being replaced by AI. This perspective also encourages the recognition of judgement beyond that provided by economic or policy optimization. It also encourages consideration of other exceptional events including failure of communication or system breaches. AI must be thought of more broadly than that which aids staff in economic and policy analysis. Although some judgement is delegated to the system, final judgement must remain with staff. It is prudent judgement to recognize the limits of the model and to respond to internal doubt by considering other judgement and expressing our judgement in writing. The model may be telling us it is economically appropriate to act, even if the extent of that action or the rationale behind that action is unclear.

Synthesis of the Literature and Research Gaps

The literature focuses on how AI can improve the information available to central banks and to a lesser extent how the improved information can be used to formulate policy. Most of the agreement on prediction is around the use of big data and advanced algorithms to reveal non-linear relationships and to produce timing signals that are not captured by traditional models (Medeiros et al., 2021). Most of the agreement on measurement is around the use of alternative (text, market and other) data to generate signals on consumer and business sentiment and expectations (Angelico et al., 2022; Araujo et al., 2024). Most of the agreement on institutional limits is around the use of machine learning to predict, but not necessarily to identify the cause or address the stability and governance issues within a system (Athey & Imbens, 2017; Mullainathan & Spiess, 2017). The remaining research gaps focus on policy, measurement and expectations. The latter is greatest for emerging markets. Research should determine if the use of AI changes the speed, asymmetry and/or the distribution of monetary policy transmission. A final gap exists regarding the interplay of AI as a tool and AI as a macroeconomic shock. Most studies explore these dimensions in the separate frameworks that central banks experience simultaneously. The same advances in technologies that better measure inflation may change the production process that generates inflation. Thus, the technological economics of AI need to be combined with the information economics of central bank forecasting and communication. Bridging the two would help better illuminate the potential transformational effect of AI on the economy's response to monetary policy.

CONCLUSION

It is more capable of synthesizing and analyzing information to see the economy more clearly by integrating AI into its public service, while keeping economic reasoning, legal responsibility and public trust within human governance. Two related channels through which AI is transforming monetary policy are described in the literature. The first is instrumental. AI allows central banks to improve their collection and analysis of large, time-varying and heterogeneous data, thereby supporting inflation forecasting and nowcasting, forming estimates of inflation expectations, analyzing communications of central banks and identifying nonlinearities in the markets and the economy. The second is more structural. AI reshapes productivity, investments, labour markets and prices and thus impacts the environment in which monetary policy operates. Complementarity is the prevailing logic for integrating AI within monetary policy. AI, based on economic theory, offers alternative ways to define and measure expectations and real economy activities. Within a theory-based framework for central bank policies, AI can help analyze and understand the data and provide new policy tools. While the same complementarity principle can also be applied to the prudent use of AI by central banks, emerging economy central banks may benefit the most from the prudent use of AI. The flexible nature of AI gives these central banks a window of opportunity to use AI to make up for their data, infrastructure and capacity deficiencies. The correct trajectory is therefore

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not automation for its own sake, but rather the governance of augmentation: AI that improves the evidence base for monetary policy while maintaining transparency, accountability and human responsibility in central banking.

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