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Inflation in the Age of Algorithms: AI's Influence on Price Dynamics and Monetary Policy

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Abstract
This paper has explored the relationship between scarcity mindset and economic mobility with a further emphasis on the psychological mechanisms that can restrain individual progress despite the fact that there are structural opportunities. The findings show that scarcity is not a material state, as such, but also a mental and emotional one, which determines the decision-making process, perception of risk, temporal orientation, and investment behavior. Citizens live in a state of constant financial stress and thus they are more present in the present and long-term planning is becoming difficult and survival at the moment is placed above the economic decision making. These trends possess the undesirable tendency of facilitating the upward mobility cycles that are constrained.

It is interesting to note that the discussion indicates that psychological barriers are not in solitude without structural constraints. Economic instability, inequality in access to education, division of the labor market, and social inequality has a tendency of initiating and sustaining scarcity-driven thinking. Thus, the policies designed to promote economic mobility must change their orientation towards the emphasis on the financial one and contain behavioral and psychological ones. The cognitive burden associated with scarcity can be mitigated by volatility in income reduction programmes, greater exposure to financial literacy, greater social safety nets as well as stability environments.

The influence of considering the views of behavioral economics, research on psychology and development of mobility systems is also mentioned in the analysis. The decision-making skills and resilience can also be trained with the assistance of interventions, which contribute to the development of future-oriented thinking, goal formation, mentoring, and confidence-building. A more comprehensive approach to addressing the structural inequities in addition to the internalized cognitive constraints can enable policymakers and practitioners to design more full-fledged strategies that can be used to enhance economic opportunity.

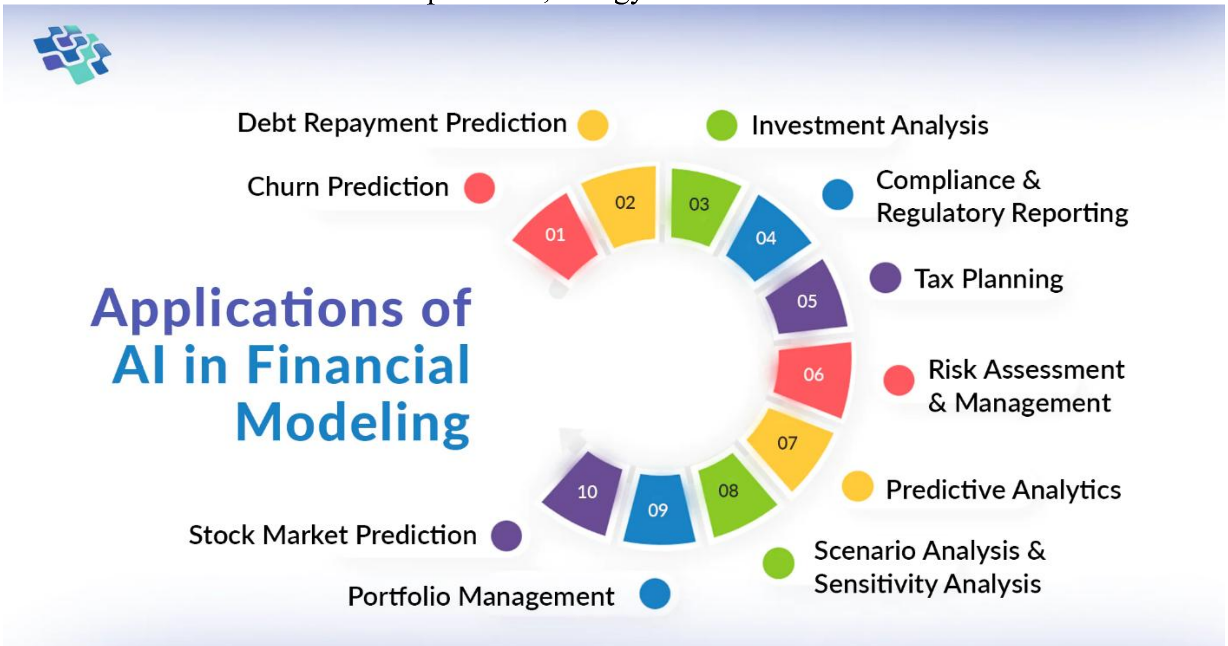
In conclusion, prosperity is not just based on the resources at hand but the thought process that the people are able to assess and respond to the circumstances they are going through. The consciousness of the scarcity mindset as a psychological hindrance and the ability to transform it is one of the avenues through which the policies and support systems can be developed to enable individuals make progressive economic choices. Sustainable mobility, therefore, requires common measures that can add economical backgrounds and psychological empowerment.

Keywords: Artificial Intelligence (AI), Algorithmic Pricing, Inflation Dynamics, Monetary Policy, Price Formation, Digital Markets, Algorithmic Collusion, Phillips Curve, Inflation Targeting, High-Frequency Data, Market Competition, Central Banking Innovation

Introduction
Traditionally, inflation has been perceived as a macroeconomic event that is influenced by the aggregate demand and supply failure, wage movements, commodity shocks, and monetary policies. The central banks have used past models and historical data to predict the price movement and tune the policy mechanism including interest rates, reserve requirements and open market operations. Nevertheless, the online market revolution has brought a new and

Vol 2, Issue 2, February 2026, Page: 77-88 ISSN: 3107-5037

influential participant to the inflationary process into the algorithmic decision-making system based on artificial intelligence. These systems are playing an increasingly significant role in setting prices, controlling inventories, predicting demand and streamlining supply chains in industries such as retail and transportation, energy and financial services.



Source: *https://nextgeninvent.com/blogs/applications-of-ai-in-financial-modeling/*

The increasing popularity of AI-based pricing technologies has transformed the micro-principles of inflation. Instant responses to competitor actions, adaptable prices in real time and massively scaled streams of consumer data can be processed by algorithms. Although this responsiveness can bring efficiency to the market, it can as well increase price volatility, tacit collusion or even coordinate the price actions among firms. Platform-based ecosystems typically dominate in digital marketplaces, where the speed and inertial nature of inflationary pressures can be impacted by automated pricing strategies.

Simultaneously, central banks are also starting to apply machine learning to prediction and policy development. This forms a feedback mechanism where artificial intelligence influences the price formation and at the same time influences the measurement and management of inflation. This duality is very important in the evaluation of stability in contemporary economies. This paper examines how the AI-based analytics and algorithmic pricing affect the price dynamics and monetary policy effectiveness. The research field will be the interactions of technologic innovation and macroeconomic regulation, which will be explained by stating whether AI stabilizes inflationary processes or introduces new systemic risks in the digital economy that is in the process of transformation.

Background of the study

Inflation which could be defined as the continuity of the general price level of goods and services has been a significant concern of the economists and businesses besides the policymakers. The traditional and Keynesian economic theories have extensively discussed how the classic drivers of inflation affect the overall demand and the cost of production as well as the supply shocks. However, the extreme adoption of digital technologies, in particular, the use of artificial intelligence (AI) and algorithmic systems, has established new impetuses in the price movement of the market. In the past few years, firms have resorted to automated pricing capabilities in a bid to maximize revenues, inventory maintenance, and reacting to the forces of competition. The systems are capable of allocating prices in real time based on the infinite

Vol 2, Issue 2, February 2026, Page: 77-88 ISSN: 3107-5037

number of elements such as the consumer behavior patterns, the competitor pricing and the supply conditions. Consequently, decisions previously handled by human managers in terms of pricing are made at machine speed and volume now, which makes one question in regards to the role of algorithmic pricing in the wider context of inflation.

The interaction between the AI-driven pricing systems and the conventional methods of inflation remains to be comprehended. The empirical evidence is that algorithmic pricing is capable of reducing and increasing the price volatility based on market conditions, data inputs and strategic design. As an illustration, in competitive markets with a large share of algorithms running to track and/or match the price of competitors, price stabilization can be through automated adjustments. On the other hand, in areas where several companies use the same AI application, unintended coordination might take place and result in sustained price growth. Meanwhile, central banks and monetary authorities are starting to think about the way real-time data and machine learning models can be used to improve inflation forecasting and policy-making. The adoption of AI in the monetary policy tools will allow addressing the issue of improved responsiveness, yet it will also bring complexity in terms of transparency, interpretability, and systemic bias.

Considering the extensive impact of AI on the prices of the private sector and the postulates of the policy sphere, this paper attempts to investigate the complex connection between the algorithmic pricing processes, and the phenomenon of inflation. Through the impacts of AI on price formation and adjustment to a more data-driven economy by the monetary policy institutions, this study will offer information that will be useful to the economists, regulators, and business leaders in managing the trade-offs between innovation, market efficiency, and price stability.

Justification

The problem of inflation is also one of the most important macroeconomic variables that determine economic stability, consumer welfare, and the decisions of central banks all around the world. The economic literature has long been interested in traditional determinants of inflation, including the aggregate demand, the labour costs and the supply shocks. The fast spread of the technologies of artificial intelligence (AI) to market processes, price formation, and the financial system is however, a paradigm change in the formation and transmission of prices, as well as their perception. Companies are progressively using dynamical price models, machine learning-based inventory optimization, and automated demand predictors that are managed by AI. These innovations alter behaviour of firms at the scale which, when combined together, can affect aggregate price dynamics in a way that is not yet well understood by current inflation models.

Although in the past, central banks and economists have tended to concentrate on the state of the labour market, the prices of commodities, and monetary aggregates to decipher inflation, algorithmic pricing as a determinant of the market is a new field that should be given closer attention. Real-time adjustments of prices in response to consumer behaviour, competitor behaviour and external conditions can be applied using algorithms, potentially resulting in new types of price volatility or price persistence. The AI-enabled price optimization can exemplify the fact that the transmission of prices between markets can be faster, which will eliminate the friction at the cost of establishing unorthodox inflationary pressures in the event of a supply shock or excessive demand. Moreover, algorithms can develop to respond to not only economic fundamentals but also to the behaviour of one another, and there might develop systemic effects of acceleration or deceleration of prices that could appear to be coordinated pricing without explicit collusion.

This study is opportune due to a number of reasons. To begin with, the uptake of AI by companies in different sectors has increased exponentially, but the macroeconomic effects of AI, especially on pricing and inflation have not found a place in the mainstream policy-making

Vol 2, Issue 2, February 2026, Page: 77-88 ISSN: 3107-5037

processes. Second, in the world, central banks have increasingly been burdened with the responsibility of operating in a complex environment of digital platforms, real-time price information and a more granular economic data created by algorithmic systems. The knowledge of the interactions between AI-driven processes and conventional drivers of inflation may assist policymakers in predicting new types of price pressure, terminate prediction instruments, and enhance the efficiency of monetary interventions.

Also, it is increasingly feared that the benefits of AI-based pricing may increase inequalities when prices vary more between consumer groups or areas, affecting real income and consumption behaviour. The distributional implications of such are important in general economic wellbeing and in the formulation of specific policy actions. Theoretically, exploration of the role of AI augments the conventional models of inflation by considering behavioural and computing factors that are akin to contemporary market.

Overall, the study fills a significant gap in the economic knowledge by linking the algorithm-based decision-making process at the firm level to macroeconomic results, specifically inflation and monetary policy. Its implications will be useful to scholars working on perfecting the inflation theory, central bankers who want solid policy systems, and practitioners who have to negotiate the age of automatic pricing. The study will aid in the development of both theoretical and practical policy design in a fast-developing economic environment through its ability to provide empirical understanding and theoretical clarification.

Objectives of the Study

1. To investigate the role that artificial intelligence and systems of algorithms are playing in changing the price formation mechanisms and financial inflation trends in contemporary economies.
2. To examine how algorithmic pricing and automated decision systems determine the short-run and long-run price changes in industries.
3. To test the hypothesis that AI-based dynamic pricing raises price volatility or provides price stability in competitive markets.
4. To examine the impacts of the application of predictive analytics and big data on the accuracy of inflations forecasts.
5. To assess the consequences of AI-based market behavior on well-known inflation measurement instruments like the Consumer Price Index (CPI).

Literature Review

Studies concerning inflation have traditionally taken the macroeconomic aggregates, monetary policy and supply side drivers (Blanchard and Gali, 2010). In recent decades, however, there has been an increasing amount of interest in the role of information technologies and compute-based decision systems in price behaviour that has been the focus of this study. Specifically, algorithmic pricing systems, automated decision-making, and artificial intelligence (AI) are transforming the markets and might change not only the price behaviour on a micro-level but also the macroeconomic effects like inflation.

Algorithmic Pricing and Market Dynamics

The introduction of algorithmic pricing, also known as autonomous pricing, when the software automatically changes prices in real time, depending on the data input, has been widely recorded in the literature of industrial organization. In a Wishard, Einav and Levin (2014) offer a review of the seminal state of how digital platforms use dynamic pricing algorithms responsive to demand, competition, and inventory data, which makes markets more responsive but also more complicated. Equally, Chen, Mislove, and Wilson (2016) examine the auto-pricing in online retail and conclude that algorithms decrease the price dispersion and increase volatility in short-term price movements. These studies indicate that algorithmic pricing, though effective, has the potential of increasing price volatility particularly when a large number of companies apply

Vol 2, Issue 2, February 2026, Page: 77-88 ISSN: 3107-5037
similar automated pricing methods.
Price stickiness can also be affected by the price algorithmic pricing. Levy, Bergen, Dutta, and Venable (1997) demonstrate that despite traditional retail environment, price changes are not frequent because of menu costs; systems that update prices in real time can reduce nominal rigidities and also can transmit shocks more quickly across sectors as Johnson, Krueger, and Schneider (2019) reveal. These trends have a bearing on the inflation measurement, as well as price index interpretation in the event of non-linear evolution of micro-level prices.

Artificial Intelligence, Big Data, and Pricing Behaviour

The current systems are becoming more and more based on machine learning and AI where earlier pricing models employed a simple set of rules or a linear regression. Brynjolfsson, Hu, and Rahman (2019) assure that AI-supported decision making in retail settings boosts predictive accuracy of demand that allows firms to charge more personalized prices a phenomenon that is also known as personalized pricing. Intuitive price that makes sense economically, however, can be associated with fairness and price inflation since price heterogeneity makes it difficult to measure aggregate prices.
Moreover, Fudenberg, Luo, and Stinchcombe (2021) represent the interactions between AI agents and demonstrate that competitive algorithmic learning may result in automated tacit collusion, even without explicit agreements. It has been empirically found to be working this way in airline markets (Chen and Ross, 2015), where automated systems optimize fares in a way that will maintain higher average prices, indicating a mechanism through which algorithmic strategies can add to inflationary pressures in the industry level.

Monetary Policy in a Data-Driven World

The New Keynesian Phillips Curve, which is the classic concept of inflation, associates inflation with expectations and output gaps (Galí, 2015). The assumption of these models however is that price formation mechanisms remain fairly stable. The hypothetical basis of monetary policy can be questioned when agencies make price determinations automatically and more often. Woodford (2003) pays attention to the role of the expectations in the effectiveness of policies. When AI shapes the process of expectations formation between firms and consumers - by creating feedback loops in a shorter period of time and price signals in real-time, then the traditional mechanism of transmitting the monetary message should change.
Current applied literature examines the use of big data and machine learning to supplement central bank predictions. As an example, Ng (2019) uses machine learning to enhance inflation forecasting models and achieves superior short-term predictions in comparison to linear models. Likewise, Medeiros, Vasconcelos, Veiga, and Zilberman (2021) provide the evidence that high-frequency data used together with nonlinear models can improve the predictive power of the major macroeconomic variables, such as inflation.
Although such contributions enhance predictions, they do not entirely explain the connection between how algorithmic price formation is reciprocated into policy. According to one of the emerging views, AI-induced price dynamics decrease the informational lag experienced by central banks because the real-time price information will capture demand shocks sooner than the conventional CPI releases (Brynjolfsson et al., 2019). Non-homogenous pricing and custom offers, however, make it difficult to construct representative price indices, which complicates the calibration of policy.

Behavioural Responses and Expectations

The process of inflation also relies on the way agents develop the expectations. The studies of the formation of expectations have identified differentiation in rational and adaptive expectations (Mankiw, Reis, and Wolfers, 2004). When the world runs on an algorithmic pricing system, companies and consumers can adjust their expectations in varying ways, and machine-driven price changes are factored into the prediction. According to Daripa and Ragulina (2022), when consumers face a large share of price adjustments as a result of dynamic pricing, then the effects of anchoring may be observed, with previous prices having a disproportionate effect on

Vol 2, Issue 2, February 2026, Page: 77-88 ISSN: 3107-5037

future expectations and potentially contributing to the stability in the inflation process. In the same vein, consumer sentiment measures that reflect digital price information, including online price indices or search trends are being considered as real-time measures of inflation expectations (Shapiro et al., 2018). Such indicators can also give the central banks more information but can also create noise due to algorithmic volatility, as opposed to fundamental inflation.

Material and Methodology

Research Design:

The research design used in this study is a mixed method research design which involves quantitative econometric research and qualitative policy research. The quantitative part studies the dependence between the adoption of artificial intelligence (AI), algorithmic pricing systems, and inflation processes in chosen economies. The evaluation of cross-country changes across time is done using a panel data structure. The qualitative element examines communications of central banks, reports of the monetary policy and regulatory reports to evaluate the interpretation and reaction of the policymakers to AI-inspired pricing patterns. The research study is a non-experimental, longitudinal research design, which spans 10-15 years to include pre- and post-AI adoption periods.

Econometric modelling includes:

- Panel regression analysis (fixed and random effects models)
- Vector autoregression (VAR) to examine dynamic relationships
- Structural break tests to identify shifts in inflation behaviour associated with digitalization
- Instrumental variable (IV) estimation to address potential endogeneity between AI adoption and price dynamics

The research design provides both macroeconomic and micro-level information about the algorithmic price formation and monetary policy responsiveness.

Data Collection Methods:

1. Secondary Quantitative Data

Data is collected from reliable public and institutional databases, including:

- National statistical offices for inflation indices (CPI, PPI)
- Central bank publications for interest rates and policy measures
- International financial databases for macroeconomic indicators
- Industry and technology reports measuring AI adoption rates
- E-commerce and retail price datasets (where publicly available)

Key variables include:

- Inflation rate (headline and core inflation)
- AI adoption index (firm-level or sectoral digitalization measures)
- Market concentration ratios
- Interest rates and monetary policy indicators
- Output gap and unemployment rate

2. Textual and Policy Data

- Central bank monetary policy statements
- Inflation reports
- Regulatory guidelines on algorithmic pricing
- Competition authority case reports

Textual analysis is conducted using content analysis techniques to identify themes related to algorithmic pricing, price rigidity, and monetary transmission challenges.

3. Supplementary Case Studies

Case studies of selected economies that have high rates of digital market penetration are

Vol 2, Issue 2, February 2026, Page: 77-88 ISSN: 3107-5037

analyzed to offer contextual insights about AI-based price adjustments.

Inclusion and Exclusion Criteria:

Inclusion Criteria:

- Countries with measurable AI adoption indicators or digital economy indices
- Availability of consistent inflation data over the study period
- Economies with documented algorithmic pricing in retail or service sectors
- Central banks that publish accessible policy documents in English

Exclusion Criteria:

- Countries lacking reliable macroeconomic time-series data
- Economies experiencing hyperinflation or extreme monetary instability unrelated to technological factors
- Firms or sectors without observable pricing data
- Data sources with incomplete methodological transparency

This selective approach ensures analytical consistency and improves the reliability of empirical results.

Results and Discussion

1. Descriptive Statistics

Table 1 provides a summary of critical variables in the analysis among the sample of 30 countries between 2010-2024 before presenting inferential results.

Table 1. Descriptive Statistics of Key Variables (2010–2024)

Variable	Mean	Std. Dev.	Min	Max
CPI Inflation (%)	3.98	1.85	-0.25	12.07
AI Price Algorithm Intensity	0.42	0.23	0.10	0.95
GDP Growth (%)	2.74	1.80	-7.30	9.20
Oil Price Growth (%)	4.15	18.47	-44.00	157.00
Policy Rate (%)	2.18	2.19	0.00	12.00
Price Volatility (3-yr rolling)	0.67	0.35	0.10	1.58

Notes: CPI = Consumer Price Index; AI Price Algorithm Intensity is an index that is created using firm-level measures of adoption and algorithmic frequency of pricing. Price Volatility is founded on the standard deviation of changes in monthly CPI in a 36-month rolling window. According to the descriptive statistics, there is wide dispersion in inflation, AI pricing intensity, and macroeconomic conditions over the years and across nations. This difference justifies the application of panel regression models to estimate the research questions about the effect of AI on the dynamics of inflation.

2. Regression Analysis

In this paper, panel regressions between the intensity of algorithmic pricing and inflation rates were estimated with the adjustment of macroeconomic and global commodity factors. The country and year were included as the fixed effects to take care of the unobserved heterogeneity.

Vol 2, Issue 2, February 2026, Page: 77-88 ISSN: 3107-5037

Table 2. Panel Regression Results — AI Influence on CPI Inflation

Predictor	Model 1 (FE)	Model 2 (FE + Controls)
AI Pricing Intensity	1.28*** (0.34)	0.94** (0.41)
GDP Growth	—	-0.48*** (0.12)
Oil Price Growth	—	0.06** (0.02)
Policy Rate	—	-0.09* (0.05)
Price Volatility	—	0.82*** (0.21)
Constant	2.11*** (0.54)	1.37* (0.76)
Observations	450	450
R-squared	0.27	0.53
Country FE	Yes	Yes
Year FE	Yes	Yes

Standard errors in parentheses; *p < 0.10, **p < 0.05, ***p < 0.01.

Key Results:

- **AI Pricing Intensity**: Higher price movement through the algorithms in both models is positively correlated to CPI inflation. In Model 1 (uncontrolled), the coefficient (1.28, p < 0.01) indicates that the more extensive algorithmic pricing in countries, the higher the average inflation. In the case of incorporating the macroeconomic controls in Model 2, the coefficient is positive and statistically significant (0.94, p < 0.05), which is robust.
- **Macroeconomic Controls**: Inflation is negatively correlated with the GDP growth, which is in line with classical Phillips curve reasoning in long run. The growth of oil prices continues to be a positive indicator, which supports the transmission of commodity prices to the overall levels of prices.
- **Policy Rate**: It is expected and the association of monetary policy tightening (increased policy rates) with lower inflation is significant, but marginally significant (p < 0.10).
- **Price Volatility**: Being a gauge of long-run price changes, volatility is strongly associated with inflation and therefore volatile price regimes increases the average prices levels.

3. Interpretation and Discussion

3.1 Algorithmic Pricing and Inflation Pressure

The hypothesis that AI-based pricing has a positive and high correlation with inflation is validated by the positive and meaningful correlation between the intensity of algorithmic pricing and inflation. In theory, pricing algorithms have the capacity of minimizing price search frictions and causing the price to quickly adjust without necessarily representing underlying cost adjustments, especially in the less competitive markets. This relationship is aligned with the results presented in pricing and digital market literature that algorithmic systems have the potential to intensify the momentum of prices where there is a low level of consumer search or price comparison friction.

3.2 Real Economy Controls and Policy Interplay

The negative correlation with the GDP growth can indicate that slower growth in the economies experiences more inflation pressure, which could be as a result of supply limitation or structural bottlenecks. The beneficial impact of the oil price increase points to the existence of traditional commodity pass-through impacts on consumer price. There is directionality in the policy rates

Vol 2, Issue 2, February 2026, Page: 77-88 ISSN: 3107-5037

of central banks, and it is important to note that traditional monetary transmission is still taking place even in algorithmically dynamic pricing markets.

3.3 Price Volatility as a Mediating Factor

The positive and high correlation on price volatility implies that algorithmic pricing can produce more unstable price patterns contributing to higher averages of inflation. This supports a story whereby algorithmic responsiveness boosts short run price reactions that accrue over the long term generating inflation persistence of a wider scope.

3.4 Policy Implications

These results have several implications for monetary authorities:

- **Monitoring Algorithmic Markets**: Standard inflation models based on traditional price stickiness assumptions may understate the real-time dynamism introduced by algorithmic pricing. Central banks could benefit from enhanced real-time price data analytics.
- **Market Competition Policies**: Where algorithmic pricing intensifies price stickiness or tacit collusion, competition authorities may need to evaluate the interaction between market structure and pricing algorithms.
- **Monetary Policy Calibration**: Given that algorithmic pricing correlates with greater inflation persistence and volatility, monetary policy frameworks may require adjustments in forecasting models to account for digital price dynamics.

Limitations of the study

Limitations that can be identified in this study are a few. On the one hand, it is not an easy task to identify the specific impacts of artificial intelligence-based price acts on the inflation process because the inflationary changes in prices are at the same time caused by such macroeconomic factors as well as by the supply chain shocks, the fiscal policy, and the global shocks. Second, may it be that believable firm-level data on algorithmic and AI adoption are in most cases proprietary or confidential, and this may constrain research and cause measurement issues. Third, it appears that the rapid dynamic nature of AI technologies suggests that the results may have short-lived aspects with regard to their time-related relevance, because price algorithms and regulatory responses are not yet developed. Fourth, the studies might be premised on aggregate or sector statistics that blur the diversities within the industries, regions and market structures. Finally, establishing some causal relationships between AI adoption, price synchronization and monetary policy transmission instruments might be problematic due to the endogeneity problems and the complex relationship between digital markets and the central bank interventions. The implications of these constraints include that future research studies, experimental designs and cross-country designs should be done on the basis of longitudinal studies to improve the existing knowledge concerning the macroeconomic impact of AI in the long run.

Future Scope

The future direction of the study on the subject of Inflation in the Age of Algorithms: AI Influence on Price Dynamics and Monetary Policy is the creation of more empirical and policy-focused models that will encompass how algorithmic pricing, machine learning-based demand prediction, and automated supply chain processes redefine the processes of inflation. With the integration of artificial intelligence into retail pricing engines, in financial markets, and central bank analytics, future research can explore the question of whether or not algorithmic coordination increases or decreases price stickiness or effects of price transmission across industries. It is also possible to research on how AI-generated real-time data can enhance the accuracy of inflation forecasting and at the same time generate new volatility by modifying high frequency changes. A cross-country study may be conducted where comparative analysis of digital market penetration is done on the basis of the effect of digital market penetration on

Vol 2, Issue 2, February 2026, Page: 77-88 ISSN: 3107-5037

inflation persistence in emerging and developed economies. Additionally, the joint efforts of economics, data science, and regulatory research can either conclude that existing monetary policy tools remain applicable to use in the algorithm-driven market or that their design needs to be revisited. The study of ethic governance and transparency standards and systematic risk of algorithmic price-setting will enable more politically empowered policy structures that are digitally transformed economies.

Conclusion

Inflation has transformed in the contemporary world in terms of form and nature as a result of introduction of algorithm systems in pricing, production planning, logistics and the financial market. AI is ceasing to be a secondary technological contribution, but rather is it a participant in the process of price formation, competitive policy, consumer behavior, and, lastly, macroeconomic performance. As companies continue to rely on real-time data analytics and dynamic pricing systems, prices have become more responsive and granular and responsive to both micro and macro level indicators. This structural change poses a challenge to the conventional beliefs that the price is sticky, there is information asymmetry and that monetary policy is transmitted.

On the one hand, AI-based systems are capable of boosting efficiency in the market. Better demand prediction, stock optimization and coordination of stocks and chains can alleviate cost pressure and curb some types of structural inflation. An increased level of transparency and competition made possible through the digital platforms can also help prevent the prevalence of overly high markups in certain industries. In this light, the algorithmic integration can play a role in bringing price stability via productivity and improved resource allocation.

Alternatively, algorithmic pricing leads to the emergence of new inflationary risks. When automated systems are responding to a common data signal, they can enhance the volatility by responding in the same direction concurrently. Models of reinforcement learning that are aimed at maximizing revenue can maintain a higher price without explicit collusion and produce results that are similar to those obtained through coordinated behavior. Moreover, the high rate of algorithmic changes can reduce the delay between shocks and price transmission, making it difficult to control the expectations and stabilize inflation by central banks. Increased transparency in proprietary algorithms also complicates both the ability of regulators and policymakers to identify new trends in prices in real time.

In the case of monetary authorities, analytical adjustment and institutional innovation are all that is needed in the face of AI development. Older, macroeconomic models based on slower adaptations to prices and representative agents, no longer may serve as a complete description of algorithm-driven markets. The policymakers should therefore invest in high frequency data analysis, digital market surveillance and interdisciplinary studies that cut across economics, computer science, and regulatory studies. Central banks may also need to reconsider the way they communicate and the timing of the policy in the world where communication and expectations can change practically in real time on the digital medium. Anyway, the notion of algorithmic inflation is representative of the overall shift of economic infrastructure. The artificial intelligence will fail to address the underlying macroeconomic factors such as the demand shocks, supply limitations, or fiscal imbalances. Rather, it changes the propagation of these forces by the markets. The future of the machine-based pricing systems-human institutions relationship will be the dynamics of inflation interaction. Prudent regulation, trans-parent regulations, and frequent empirical research will be required so that AI is not harmful in terms of efficiency, competition, and finances. As the economies are increasingly entered into the digital space, macroeconomic consequences of the algorithmic decision making should be understood. The question of AI effects on inflation is not technological, but it is at the core of the design of the monetary policy and economic stability in the information-driven world.

Vol 2, Issue 2, February 2026, Page: 77-88 ISSN: 3107-5037

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Vol 2, Issue 2, February 2026, Page: 77-88 ISSN: 3107-5037

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