EFFECTS OF INFORMATION TREATMENTS ON HOUSEHOLD INFLATION EXPECTATIONS IN INDONESIA: A GENERATIVE AI EXPERIMENT

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Abstract

This paper introduces a novel simulation framework for modelling economic expectations and presents findings on the formation of inflation expectations. The study employs generative Artificial Intelligence (AI) Large Language Models (LLMs) to replicate the responses of human-based inflation expectation surveys in Indonesia. Based on the simulation of 5,400 household personas representing diverse demographic and socio-economic groups generated by GPT-4, we examine how different treatments of information affect one-year-ahead inflation expectations. Results show that information continuously offsets the inflation overestimation bias of households, with optimum anchoring performed by communicating the full policy context. The results further highlight heterogeneous responses with increased sensitivity to information across urban and financially literate subgroups. Cross-model comparison between GPT and Gemini yields consistent effects, highlighting robustness. While AI simulations cannot fully capture the psychological-emotional richness of expectation formation, this study validates the feasibility of using LLMs as experimental instruments for testing communication strategies and expectation anchoring mechanisms.

Keywords: Inflation Expectation, Large Language Models, Information Provision, Survey Experiment, Forward Guidance, Heterogeneous Treatment Effects
JEL: C90, C14, E27, E31, E58, E71, D84

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I. Introduction and Research Questions

Inflation expectations are a key contributor to economic stability and are a primary channel through which monetary policy impacts the real economy and financial market, signaling central banks' credibility. Inflation expectations are also affecting all sorts of expectations from economic agents, as they influence households and firms' intertemporal decision-making regarding consumption, saving, investment, and wage-setting (Coibion et al., 2020a). At the same time, for central banks, anchoring inflation expectations has become a fundamental policy objective. Anchored expectations enhance monetary policy effectiveness in avoiding transitory shocks from generating persistent deviations from the target and enhance the economy's resilience to shocks. Besides, the credibility of monetary policy is not only measured in the ability to keep inflation low and stable, but also in the management expectations of the public regarding the future trajectory of prices (Bems, et al., 2021).

Household inflation expectations are generally highly heterogeneous, context-dependent, and subject to systematic bias (D'Acunto et al., 2024). Households are far more likely to extrapolate based on recent price changes, to overweight highly salient goods like food and fuel, and to develop upward-biased inflation expectations than professional forecasters (D'Acunto et al., 2025). This poses a challenge for policy considerations, as the more unanchored or misinformed inflation expectations are, the less effective the transmission of monetary policy is, and could also increase the persistence of inflationary pressures (Coibion and Gorodnichenko, 2025).

In contemporary monetary policy, managing inflation expectations is as necessary as controlling inflation itself. For decades, secretive central banks and a lack of transparency to the public were not a problem, but this has changed substantially. In recent years, central bank communication has been critically important for influencing market expectations and shaping economic behavior (Blinder et al., 2008; Woodford, 2005). Clear, transparent communication of policy decisions today is viewed as integral to establishing credibility and anchoring expectations. However, the challenge facing central banks is not just formulating policies but communicating policies in a way that economic agents will interpret and respond adequately to the economic and monetary policy goals.

This is particularly salient for emerging economies such as Indonesia, given their high susceptibility to domestic and global economic shocks and historically high inflation volatility. Indonesia has made considerable strides in achieving price stability, successfully reducing inflation to single digits in recent years, largely due to the adoption

of an Inflation Targeting Framework (ITF) in 2005, which has been instrumental in stabilizing inflation expectations. Therefore, understanding inflation expectations is crucial as it can create a self-fulfilling dynamic that drives actual inflation rates. Bank Indonesia actively monitors inflation expectations through various survey instruments targeting different economic agents, including consumers, retailers, firms, and professional economists. Yet, the availability of systematic data on household inflation expectations has become more limited following the discontinuation of Bank Indonesia's regular household inflation expectations survey in 2020 due to disruptions associated with the COVID-19 pandemic.

The discontinuation of the household inflation expectations survey has left a gap in high-frequency direct measures from households. Furthermore, Indonesia's demographic and geographic diversity could lead to variation in inflation expectations across groups. Alternative inflation expectation data sources, e.g., business surveys, do provide some insight, but these are often less granular and may not fully capture how households form long-term or anticipatory expectations. Therefore, in the pursuit of understanding and influencing inflation expectations, household inflation expectations in particular, developing a new robust method to measure household inflation expectations is essential. In the absence of a household expectation survey, this study aims to generate household inflation expectations with agents through large language models (LLMs). For Indonesia where comprehensive household surveys can be logistically challenging and expensive to administer across the archipelago's diverse regions, LLMs using AI-based methodologies offer potentially valuable complements to traditional data collection approaches and the potential to transform methodological approaches to linguistic data analytics (Barros et al., 2024).

Recent research demonstrates that LLMs can effectively simulate how economic agents behave under different information conditions (Horton, 2023; Zarifhonarvar, 2024; Denes et al, 2021). Generating household inflation expectations using LLMs enables us to control and scale different communication treatments. We analyze the impact of information intervention and obtain its causal effect on household expectations to answer three questions. *The first* question examines the extent to which different types of information, such as those from central banks and media, influence the one-year-ahead inflation expectations of simulated Indonesian households relative to receiving no information. *The second* question investigates whether communicating Bank Indonesia's inflation target or policy rate signal is more effective in anchoring expectations compared to communicating only the current inflation rate. *The third* question explores the

heterogeneity of these treatment effects across simulated households with differing demographic and socio-economic characteristics, reflecting Indonesia's diversity.

Utilizing AI generative models GPT and Gemini AI to simulate household responses, we have succeeded in generating 5,400 individual personas' inflation expectations for each quarter from 2018 until 2025. These personas represent different demographic and socio-economic groups across Indonesia. The analysis demonstrates that the provision of relevant policy information mitigates households' tendency to overestimate future inflation systematically. Among the various communication strategies assessed, the dissemination of a comprehensive policy context was found to exert the strongest anchoring effect, followed by the communication of the inflation target. The results further indicate that the influence of information treatments is not uniform across the population, with more pronounced effects observed among households residing in urban areas and those exhibiting higher levels of financial literacy. These findings, consistent with research by D'Acunto et al. (2019), highlight substantial heterogeneity in the effects across demographic groups, wherein policy communications tend to influence some segments of the public. Moreover, Bayesian learning analysis suggests that respondents learned most from explicit communication about targets and policy frameworks, rather than communicating only the inflation target or policy rate decision. These findings carry important policy implications, suggesting that monetary authorities can enhance credibility and improve the effectiveness of monetary transmission not only through consistent and transparent communication, but also by adopting more targeted approaches tailored to different demographic and socio-economic groups. Our findings lead to several discussions considering that less informed individuals often monitor only salient prices, e.g., food and regulated-goods prices, complicating the central bank's efforts to effectively communicate policy to them due to their behavioural tendencies.

The paper is structured as follows. Section II gives an overview of recent literature, along with the economic theory of inflation expectation and Generative AI studies. Section III will discuss the data and methodology used to generate the experiment, as well as the model and robustness check. Sections IV and V provide the results of the experiments, discussions, and a conclusion of the findings.

II. Literature Review

Inflation expectation is a key component of economic modeling and in shaping economic behavior and policy. This area of study examines the psychological and informational

aspects of how economic agents form and predict their future inflation expectations. Recent studies demonstrate the significance of inflation expectations on inflation and its determinants. The previous study by Coibion et al. (2019) suggests that informing households of the Federal Reserve's inflation target can significantly shift their inflation expectations with an effect size comparable to reading an entire Federal Open Market Committee statement. Similar research by D'Acunto et al. (2019) highlights substantial heterogeneity in the effects across demographic groups, wherein policy communications tend to influence some segments of the public more than others and impact how people update their forecasts after receiving information. These studies confirm that one potential tool for managing expectations is by providing sets of information to the public to guide their inflation outlook.

In recent years, AI has emerged as a more powerful tool in economic research and policy analysis. AI presents new approaches to modeling behavior, predicting macroeconomic factors, and evaluating policy interventions. International financial institutions have also recognized the potential of AI in strengthening policy design and communication, emphasizing its capacity to enhance forecasting and improve the timeliness of policy responses (BIS, 2021; IMF, 2021). In addition, AI-based simulations provide exciting possibilities for constructing synthetic economic agents, which enable the study of expectation formation and estimating inflation expectations under diverse demographic and informational conditions (Horton, 2023; Zarifhonarvar, 2024) —an area traditionally informed by surveys, econometric models, and financial market indicators. Some previous studies have explored how machine learning and natural language processing (NLP) techniques are applied to analyze textual data, to infer public sentiment and expectations regarding inflation or inflation forecasting (Denes et al, 2021; Shcherbakov & Karpov, 2024).

Large Language Models (LLMs) have emerged as useful tools in economic research, augmenting modeling, forecasting, and behavioral analysis in ways that increasingly parallel or surpass traditional methods. The introduction of LLMs, such as GPT and Gemini AI, has significantly transformed economics research, especially its capabilities in simulating complex economic scenarios and their broader implications for economics (Akata et al., 2023; Charness et al., 2023; Korinek, 2023). Brookins and DeBacker (2023) show that GPT agents mimic human tendencies for fairness and cooperation and sometimes exhibit higher rates of cooperation than humans.

Recent studies also show the significance of applying LLMs to macroeconomics research.

Li et al. (2023) use a framework using LLMs as agents for macroeconomics simulation designed for human-like decision making. Faria-e Castri and Leibovici (2023) use LLMs as a tool for inflation forecasting and show that Google AI's PaLM outperforms traditional methods when compared to the Survey of Professional Forecasters during the period of 2019-2023. Additionally, Hansen et al. (2024) simulate Survey of Professional Forecasters data using restricted and unrestricted approaches, including synthetic personas of professional forecasters, and find that AI agents exhibit a similar pattern to professional forecasters. An enhanced agent-based modelling (ABM) was developed by Zarifhonarvar (2024), which enables the creation of more sophisticated and realistic agent behavior using LLMs, concluding that LLMs can generate granular predictions of inflation expectations across demographic groups. This suggests potential applications in forecasting survey responses with limited data.

Agents update their inflation expectations by weighing prior beliefs and new information according to their level of attention. In a Bayesian learning setting, Weber et al. (2025) suggest that as inflation rises, both households and firms become more attentive to publicly available information about inflation, leading them to respond less to exogenously provided information treatments. Cavallo et al. (2017) suggest that people partially update and attach limited weight to new statistics, that the weight varies by information source and context, and that rational inattention helps explain incomplete updating.

Textual reasoning and cognitive framing in expectation formation represent an important but understudied dimension of how economic agents process information. Recent advances in Natural Language Processing (NLP) have enabled researchers to move beyond quantitative measures of expectations to examine the qualitative reasoning underlying expectation formation. Denes et al. (2021), and Shcherbakov and Karpov (2024) demonstrate that automated text analysis can extract meaningful economic signals from unstructured textual data, revealing how households and firms interpret macroeconomic conditions through distinct conceptual frames. Hansen et al. (2024) show that LLM agents not only produce numerical forecasts but also generate coherent reasoning narratives that reflect their underlying beliefs and information processing patterns. This textual dimension is particularly valuable for understanding whether information treatments produce genuine cognitive shifts or merely superficial adjustments to numerical forecasts. By analyzing concept extraction, reasoning length, and certainty language patterns, researchers can distinguish between cases where agents update their interpretive frameworks versus cases where they simply adjust point

estimates while maintaining unchanged belief structures. This approach complements existing quantitative methods by revealing the mechanisms through which information affects expectation formation at both the numerical and cognitive levels.

Using survey experiments with LLMs is suitable for examining inflation expectations for multiple reasons. *First*, measuring inflation expectations is challenging due to their process complexities and heterogeneity across economic agents (Coibion et al., 2020a; Weber et al., 2022). *Second*, inflation expectations have a significant effect on economic decisions, such as consumption, investment, and wage-setting (Coibion et al., 2020b). *Third*, the formation of inflation expectations is important for central banks to conduct their monetary policy effectively (Pfajfar and Zakelj, 2018). As studied by Jiang et al. (2024), the effect of inflation expectations is inconsistent across demographic groups, and their relationship with spending behavior is a complex dynamic process that LLMs need to capture. For these reasons, Nie et al. (2024) conclude that LLMs like GPT and FinBERT are highly effective in understanding context, processing large-scale data, and are also useful in sentiment analysis and financial decision-making.

Recent literature highlights that the complex nature of inflation expectations — their central role in the economy and the inherent challenges in measuring and predicting them—makes this topic particularly suitable for applying new methods using large language models (LLMs). This study follows the previous generative AI experiment studied by Zarifhonarvar (2024), with Indonesian economic data and mimics its human-based survey. As explored by Juhro (2015), short-term inflation expectations among Indonesian households have increased over time. Interestingly, households tend to predict higher inflation compared to other agents, such as firms and professional forecasters. This phenomenon occurs because less informed individuals often monitor salient prices, e.g., food and regulated goods prices, and behave according to this dynamic. Understanding how well households anchor their inflation expectations is vital for the effectiveness of monetary policy transmission; when the inflation expectations are not well-anchored, it may lead to second-round effects that make inflation harder to manage. Additionally, an improved understanding of household inflation expectations formation can enhance macro models used to predict future inflation.

III. Methodology and Data

III.1 Experimental Design

This section describes the experimental design, persona construction, treatment

assignment, and implementation process. This experiment consists of two main phases. The first phase focuses on developing the LLM agent's persona, and the second examines the impact of information provision treatments on AI agents. Using GPT-4.1 mini, the study begins with the development of an LLM agent simulation framework that models Indonesian households as individual agents within the computational environment model. Each agent represents a simulated household endowed with specific demographic characteristics and decision-making information sets that are informed by real-world data and behavioral economics principles relevant to Indonesian households.

The LLMs are customized with distinct persona characteristics—such as income group, education level, gender, and geographic region—to emulate the heterogeneity observed among Indonesian households. These personas are designed to demonstrate systematic biases in inflation expectations that mirror patterns observed in human survey responses. This suggests effective information treatments in Indonesia must account for the country's diverse demographic composition, spatial disparities, heterogeneous information access, and potential partisan divides across different population segments. These characteristics have been shown to shape inflation perceptions and expectation anchoring (Bank Indonesia, 2023; Juhro and Goeltom, 2023).

In addition to these demographic determinants, agents' inflation expectations can be significantly influenced by their level of media exposure and financial literacy. The amount of exposure an agent receives from media is shaped by interactions among several elements, such as demographic and social factors, as well as media characteristics (Lobo and Bhat, 2023). Agents with higher socioeconomic and educational resources are more likely to have richer and more diverse media repertoires or exposure (Leuppert et al., 2024). Financial literacy is likewise influenced by a combination of demographic and socioeconomic factors such as educational level, income, age, and occupational status, in which both financial literacy and education levels are positively and significantly related to agents' savings and financial behavior (Rehman and Mia, 2024; Yoshino et al., 2017). Therefore, media exposure and financial literacy could provide additional insight into explaining how agents form their inflation expectations.

A crucial element of this framework is the integration of an LLM to enable the agents to process information in a more nuanced and context-aware manner, mimicking human-like understanding and interpretation of the information provided. This simulation-based experiment is designed to analyze the impact of information on inflation expectation, mimicking Bank Indonesia's discontinued household inflation expectation

survey. Therefore, the simulation-based experiment distribution sample follows Bank Indonesia's discontinued household inflation expectation survey; for example, the composition of respondents' gender consists of 38.9% male and 61.1% female respondents. This composition is also consistent with previous research findings showing that female participation in surveys is often higher than that of males (Wu et al., 2022; Becker, 2022).

To allow for comparison with past survey data, the experiment is simulated to start at Quarter 1 of 2018 up to Quarter 2 of 2025. Demographic personas are assigned to simulated agents based on gender, age, education, income level, region, and their location (urban/rural) as described by Table 1. Many of these variables are correlated with each other. For example, income is generated from expenditure to ensure continuity and accuracy on each agent's economic status, reflecting the actual distribution of household expenditures in Indonesia.

Table 1 Generated Persona Variables for Each Agent

Variable	Description
Age	20 to 80 years old
Gender	38.9% Male, 61.1% Female
Education	Senior High School, Diploma, Bachelor's degree, Master's degree
Expenditure Bracket	(Rp1,000,000-Rp2,000,000), (Rp2,100,000-Rp3,000,000), (Rp3,100,000-Rp4,000,000), (Rp4,100,000-Rp5,000,000), (Rp5,100,000-Rp6,000,000), (Rp6,100,000-Rp7,000,000), (Rp7,100,000-Rp8,000,000), (> Rp8,000,000)
Expenditure	Rp1,000,000 to Rp20,000,000
Region	Java (56%), Sumatra (22%), Kalimantan (6%), Bali-Nusra (5%), Sulampua (11%)
Province	All of 38 provinces in Indonesia
Urban/Rural	Urban (56%), Rural (44%)
Financial Literacy	Score from scale of 1-10 with 1 being the lowest and 10 being the highest. Determined from education level and income.
Media Exposure	Score from scale of 1-10 with 1 being the lowest and 10 being the highest. Determined from education level and whether persona is from an urban or rural area.
Risk Attitude	Score from scale of 1-10 with 1 being the risk averse and 10 being risk loving. Normally distributed with a mean of 5.5 and standard deviation of 1.8 (Sahm, 2012).

The core of the experiment revolves around the implementation of carefully designed information treatments. We simulate our agents based on the latest Bank Indonesia's consumer survey, including the composition of the persona's demographic. This involves dividing the simulated households into several distinct groups, i.e. multiple treatment groups and a control group. Each treatment group would be exposed to a specific piece of information directly related to inflation or factors influencing it, while the control group would not receive such information during the experimental period. The deliberate and systematic design of these information treatments is essential for isolating the causal effects of specific types of information on the inflation expectations of the simulated households. Different types of information, varying in their source, content, and framing, could potentially elicit diverse responses from the agents.

To assess the impact of information treatments on household inflation expectations, the model would require a robust mechanism for measuring the inflation expectations of the simulated households. The simulation-based experiment, with AI Agents in structured surveys and predictive modelling, eliciting points of predictions, reasoning, and probability of distributions. The experimental design, as shown in Figure 1, proceeds through three consecutive stages: pre-treatment, treatment, and post-treatment. ***In the pre-treatment stage***, each LLM agent is given two baseline questions: Question 1, eliciting quantitative inflation expectation in point of prediction for one-year-ahead expectation, and Question 2, capturing the qualitative narrative underlying the agent's expectation. These responses establish each agent's prior beliefs and rationale before any exposure to other external information. This study will exhibit the inclusion of the control group as a baseline model, which serves as a benchmark against which the behavior of the treatment groups can be compared. ***At the treatment stage***, the agents are then randomly assigned to different information treatments, which are designed to simulate real-world information environments, such as macroeconomic news, central bank communications, or neutral information. These treatments are intended to replicate various forms of information which households might encounter in actual environments. ***In the post-treatment stage***, agents are presented with similar questions as in the pre-treatment stage to evaluate the effect of information treatment on agents' inflation expectation. Comparing pre-treatment and post-treatment responses enables the identification of changes in inflation expectations and quantitative reasoning attributable to the information exposure. This allows the results to be isolated from the specific effect of the information treatments or any other factors within the simulation that might independently influence inflation expectations over time.

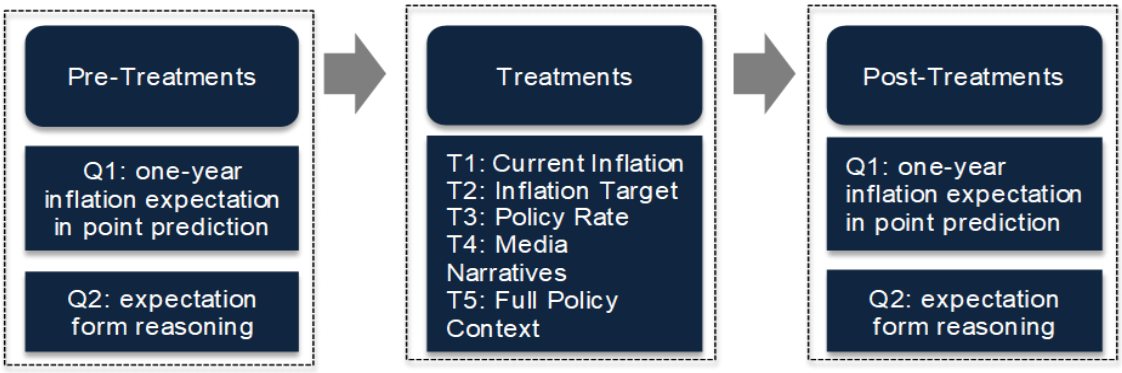


Figure 1 An Overview of Survey Experiment Design

Building upon the experimental framework previously described, a detailed overview of the specific information treatments given to each agent group throughout the simulation is provided in Table 2. Each treatment group is exposed to a different type of information, which consists of current inflation information, inflation target, central bank's policy rate decision, media narratives, and full policy context, while the control group receives no information at all and serves as a base case. The table details the content, source, and framing of each treatment, as well as the timing and frequency the agent is exposed to, which will greatly affect agents' responses (Horton, 2023; Hansen et al., 2024). By systematically varying information treatments, the experiment captures the heterogeneous effects of information on both quantitative inflation expectations and the qualitative reasoning underlying expectations across demographic personas. This is consistent with prior research showing that the source, content, and framing of information have a distinct effect on inflation perceptions and expectation formation (Bank Indonesia, 2023; Juhro and Goeltom, 2023; Denes et al., 2021). The information structure of treatments presented in Table 2 also provides a transparent framework for assessing causal impacts in the simulation, enabling comparison of responses in pre-treatment and post-treatment.

Table 2 Summary of Information Treatments

Information Treatment Type	Specific Content of the Treatment
Controlled	No additional information. The agent simply forecasts inflation without any new input
Current Inflation Information	Inflation rate of the past period
Inflation Target	Recent news about the current target of inflation by Bank Indonesia and the government
Central Bank's Policy Rate Decision	Represents the signal of monetary policy stance. This isolates the effect of hearing about a monetary policy action, focusing on the signal content of Bank Indonesia policy rates (BI Rate)
Media Narratives	The summary of latest news from global and Indonesia economic situation
Full Policy Context	Summary of the economic policy stance, including GDP, inflation rate, inflation target, interest rate, USD/IDR exchange rate, food and energy policy change, as well as a summarized economic outlook for a specific quarter.

The experiment is conducted with the following steps. *First*, we generate 30 agents to be randomly assigned to each treatment type for each quarter. For all samples we have 5,400 personas with 180 agents generated for each quarter. The agents will be asked for their initial inflation expectation over the next year and their reasoning based on their specific personal background. All personas received their information in simple, person-friendly language (in English) to mimic how real households might encounter such information in media. *Second*, assigned treatments are applied to the agents through an LLMs prompt. We specified the prompt with the agent's demographic persona, specific quarter, and year, and the assigned treatments. Towards the end of the experiment, the agents are asked for their post-treatment inflation expectation and reasoning. The responses are collected in structured JSON (JavaScript Object Notation) format, with numerical inflation expectations parsed as percentages and open-ended reasoning stored for qualitative analysis. The difference between initial expectation and post-treatment expectation is then retrieved as a dependent variable in our model to determine the causal effect of each information intervention on inflation expectations and conduct a heterogeneity test based on their different demographic personas. Table 3 shows the flow of the survey experiment and the main prompt applied in each stage.

Table 3 Flow of the Survey Experiment

Stage		Prompt
Main Prompts	Specific Persona	You are a {self.age}-year-old {self.gender} living in a {self.urban_rural} area in {self.province}, {self.region} region of Indonesia. We are currently in {self.quarter}. Your highest education level is {self.education} and your monthly income is around Rp {self.income:,.0f}, which is considered {income_level} income. Your household expenditure bracket is {self.expenditure_bracket} per month. Your financial literacy level is {self.financial_literacy}/10 and your exposure to economic news media is {self.media_exposure}/10. You have a {self.risk_attitude}/10 risk attitude (where 1 is very cautious and 10 is very comfortable with risk).
	General	You are simulating the economic thinking and inflation expectations of an Indonesian citizen with the following characteristics: {self.persona.to_prompt_description()} Your task is to realistically role-play this person's economic views and expectations, considering their background. Some important economic contexts about Indonesia: - Indonesia is the largest economy in Southeast Asia - Indonesia's central bank is Bank Indonesia (BI) - The economy is diverse but still reliant on natural resources and agriculture in many regions - Bank Indonesia sets interest rate policy to control inflation Please respond as this person would, considering their education level, financial literacy, and background.
Pre-treatment Questions	Prompt	"I'd like to ask you about your expectations for inflation in Indonesia over the next year. Given your understanding of the economy and recent trends, what percentage do you expect prices to increase by in the next 12 months?" Please provide your response in JSON format with the following fields: 1. inflation_expectation: Your numerical estimate of inflation (as a percentage) 2. confidence: How confident you are in this estimate (1-10 scale) 3. reasoning: A brief explanation of your thinking
	Example	"inflation_expectation": 4.5, "confidence": 7, "reasoning": "I think inflation will be moderate because..."
Treatments	Example	full_policy_context': f""" Bank Indonesia has announced its policy stance: - Current inflation: {context['current_inflation']}%

Stage		Prompt
		- Policy interest rate: {context['policy_rate']}% - Inflation target: {context['inflation_target']} - GDP growth: {context['gdp_growth']}% - Economic outlook: {context['economic_outlook']} - IDR/USD exchange rate: {context['rupiah_exchange_rate']}
Post-treatments	Prompt	You recently received the following information about the economy: {self.memory['treatment_received']['content']} Considering this new information along with your prior knowledge: message = f""" {treatment_info} "What percentage do you now expect prices to increase by in Indonesia over the next 12 months?"

III.2 Large Language Model Prompt Design

We operationalize the survey experiment through a three-layer prompt stack, namely (i) a system prompt that anchors role-play and Indonesian macro context, (ii) stage-specific user prompts for pre-treatment and post-treatment questions, and (iii) treatment inserts that deliver randomized information to agents. Responses are constrained to a strict JSON schema (numeric point forecast, confidence, and free-text reasoning), which the pipeline parses downstream. For every agent, we instantiate a persona-conditioned system prompt that (i) asks the model to realistically role-play an Indonesian household with specific demographics, and (ii) injects concise macro context such as the role of Bank Indonesia, policy rate function, and structural features of the economy. This prompt is programmatically constructed and includes the persona description output. This design keeps the macro frame constant while allowing the demographic to vary.

For the first stage, we ask the agents the pre-treatment question. Agents first receive a neutral, persona-aware question eliciting a 12-month-ahead point forecast of inflation, output in JSON with fields inflation expectation (in percent), confidence (scale 1–10), and reasoning with a brief explanation. This mirrors the flow and schema specified in Table 3 and is enforced again in code during calls to predict inflation expectation. *Second stage*, after the baseline, we proceed to treatment delivery. The assigned information treatment is appended as a content block before the post-treatment question. Treatments are templated strings that substitute quarter-specific context (e.g., current inflation, policy rate, target, GDP growth, exchange rate, and a short economic outlook). The post-treatment prompt references the exact content previously shown to the agent to minimize

drift and ensure within-agent comparability. *At the third stage*, we finally conduct the follow-up steps and re-elicit the 12-month-ahead forecast with the same JSON schema and explicitly instruct the agent to incorporate the just-seen information, enabling us to compute within-agent expectation changes for causal estimation.

At run time, each message bundle contains: (i) the persona-anchored system prompt, (ii) a stage-specific user prompt (pre or post), and (iii) when applicable, a treatment insert. The prompts and the JSON schema mirror the flow of the Survey Experiment shown in Table 3, including the persona preamble and the JSON output contract. For modeling choices and guardrails, we adopt a lightweight schema-first pattern to reduce free-form output variance. The prompt includes: (i) a minimal Indonesian macro primer to reduce hallucinations; (ii) explicit JSON field names and an example; and (iii) reminders to answer "as the described person" to keep outputs aligned with demographic characteristics. In code, the same JSON contract is requested at both stages to standardize parsing and downstream differences.

III.3 Persona Features

Each AI agent represents a synthetic Indonesian household. Personas are generated quarterly and encode demographic and behavioral heterogeneity known to correlate with inflation perception. The Persona object (data class) includes id, quarter, age, gender, education, income, region, province, urban-rural, financial literacy, media exposure, risk attitude, expenditure bracket, and expenditure. Personas follow Indonesia-consistent demographic variable distributions and are regenerated per quarter as follows:

a. Age: 20–80, sampled by province-specific brackets, then mapped to an exact age within the bracket.
b. Gender: sampled by target shares (≈ 38.9% male, 61.1% female as in Table 1).
c. Region & Province: 38 provinces nested within five macro regions (Java, Sumatra, Kalimantan, Bali-Nusra, and Sulampua).
d. Urban/Rural: base shares with province-level overrides (e.g., higher urban probability for Jakarta; lower for some eastern provinces).

Personas also follow Indonesia-consistent socio-economic characters, behavioral information, and distributions, which are regenerated per quarter as follows:

a. Expenditure bracket & expenditure level: brackets (Rp1–2m, Rp2.1–3m, …, >Rp8m) with continuous expenditure drawn within the bracket.
b. Income: inferred from expenditure bracket with multiplicative adjustments by

education and urban/rural status; random draw within adjusted range. This ensures consistency between living standards and income proxies.

c. Financial literacy (1–10): based on education with positive adjustment for income exposure; clipped to [1,10].
d. Media exposure (1–10): base by education with location adjustment (urban > rural) and small noise; clipped to [1,10].
e. Risk attitude (1–10): normally distributed around 5.5 (Sahm, 2012) with clipping.

These characters align with the variable descriptions and scale choices specified in Table 1. Each persona carries a quarter tag and a unique id, ensuring one-to-one mapping between the forecast record and the agent's demographic state for that period. Persona generation stitches all fields in a single pass to maintain internal consistency. The persona object provides a human-readable description via a prompt description, which is embedded into both the system prompt and the stage prompts; this creates a consistent "voice" across pre- and post-treatment stages and reduces within-agent drift. In Table 3, this appears as the "Specific Persona" block (age, gender, location, education, income/expenditure, financial literacy, media exposure, risk).

III.4 Empirical Model

To empirically assess the impact of treatments on agents' inflation expectation, we estimate a model with three different Ordinary Least Square (OLS) specifications. First, to estimate the effect of any treatment on agents' inflation expectation change. The results will show the magnitude of the adjustment made by the agent after given the information treatment. Second, we test the heterogeneity across the agents' demographic characteristics with treatment effects as control. The hypotheses are the effect will vary among the agents; depends on the persona they pose. Third, we apply the interaction term for each treatment on agents' demographic persona. All the models applied heteroskedasticity-robust standard error and estimated as follows:

$$\left(EXP_{i,t}^{post} - EXP_{i,t-1}^{pre}\right) = \alpha + T_{i,t}'\gamma + (D_i . T_i)'\delta + e_{i.t} \quad (1)$$

$$\left(EXP_{i,t}^{post} - EXP_{i,t-1}^{pre}\right) = \alpha + D_{i,t}'\beta + T_{i,t}'\gamma + u_{i.t} \quad (2)$$

$$\left(EXP_{i,t}^{post} - EXP_{i,t-1}^{pre}\right) = \alpha + D_{i,t}'\beta + T_{i,t}'\gamma + (D_i . T_i)'\delta + \varepsilon_{i.t} \quad (3)$$

where $EXP_{i,t}^{post} - EXP_{i,t-1}^{pre}$ represents the AI agents' expectation change after and before treatments, respectively. $D_{i,t}'\beta$ is a demographic column vector for each persona, $T_{i,t}'\gamma$ is a

column vector of treatments, and $(D_i.T_i)'\delta$ denotes all interaction variables between each persona and the treatments. β and γ are coefficient vectors measure the impact level of demographic persona and each treatment on inflation expectation change, respectively, while δ is the coefficient of interaction variables.

The regression results will show that the effects of treatments are different for divergent demographic characteristics. For the sake of econometric robustness, we followed general model diagnostic tests, such as R-squared and adjusted R-squared, normality test, and autocorrelation test. Lastly, a robustness check is conducted by testing the reliability of the agent-based model inflation expectation household survey using other LLMs, Gemini AI 2.5- flash. In addition, to ensure our simulated survey can mimic and exhibit a similar pattern to a human-based survey, we compare simulated results from GPT and Gemini AI with available human-survey data, namely the actual consumer survey for the 2018-2019 period and the retail survey for 2020 onward. This empirical model evaluation will help us understand how AI agents change their prior beliefs about inflation expectations and quantify the adjustments made in their post-treatment decisions based on different demographic personas.

III.5 Bayesian Learning

Further analyses are conducted to quantify belief updating in response to specific information treatments when agents form their inflation expectations. Weber et al. (2025) provide a rigorous and theoretically grounded framework for measuring attention to inflation through RCTs. The central idea is to assess how strongly individuals adjust their beliefs after receiving an information treatment, relative to how strongly they are anchored in their prior expectations. The key contribution of the framework is the scaled treatment effect (γ/β), which captures the extent to which individuals incorporate new information into their beliefs, also reflecting both the responsiveness to new signals and the share of previously uninformed individuals. This measure is comparable across different treatments, countries, and time periods, while varying systematically with the economic environment, particularly the level of inflation. The core empirical specification is:

$$posterior_i = \alpha + \beta prior_i + \delta I_i + \gamma(I_i \, x \, prior_i) + \varepsilon_i \qquad (4)$$

where *prior* is pre-treatment inflation expectation, *posterior* is a post-treatment inflation expectation, *I* is a treatment indicator (1 if treated, 0 if control), and β, γ, δ denote weight on priors for the control group (baseline anchoring), change in slope for the treatment group (treatment effect on updating), and level shift from treatment, respectively.

III.6 Textual Reasoning Analysis

Beyond capturing numerical shifts in inflation expectations, this study also explored how information treatments influenced the qualitative reasoning behind those expectations. Specifically, we analysed the textual explanations generated by AI agents before and after each treatment to uncover changes in the cognitive framing, conceptual focus, and confidence levels embedded in their reasoning. This provided a deeper understanding of how different types of information shaped not just what agents believed about inflation, but why and how they formed those beliefs.

The analysis proceeded through three main dimensions. *First*, we performed concept extraction to identify recurring economic themes within the reasoning texts. Using regular expressions, we detected mentions of inflation, government policy, currency valuation, wages, consumption, savings behaviour, and personal economic experience. This enabled us to systematically compare the conceptual content of responses before and after treatment. By examining how often certain concepts appeared across different treatment groups, we could assess whether the interventions triggered more behavioural, policy-aware, or financially grounded reasoning.

Second, we measured reasoning length as a proxy for cognitive elaboration. For each agent, the average number of characters in their textual explanations was calculated both pre- and post-treatment. An increase in length was interpreted as a sign of more detailed or reflective thinking, while a decrease suggested more concise or potentially heuristic-based reasoning. This helped us infer whether the information provided encouraged deeper analysis or reinforced quick, confident judgments.

Third, we conducted certainty language detection to evaluate changes in epistemic tone. We classified words and phrases expressing varying levels of confidence—ranging from high-certainty markers (e.g., "definitely," "will," "must") to hedging or low-certainty language (e.g., "might," "could," "I think"). This allowed us to quantify whether agents expressed greater or lesser confidence in their explanations after receiving specific types of information.

Altogether, this textual reasoning analysis offered a structured and reproducible method for evaluating the qualitative impact of information treatments. It showed whether the interventions influenced not only the magnitude of expectation changes but also the cognitive structure and stylistic tone of economic reasoning. Thus, it complements the quantitative findings by revealing shifts in how agents articulate their understanding—

whether more behavioural, analytical, or experiential—as a response to different informational frames.

IV. Results and Discussion

IV. 1. Results

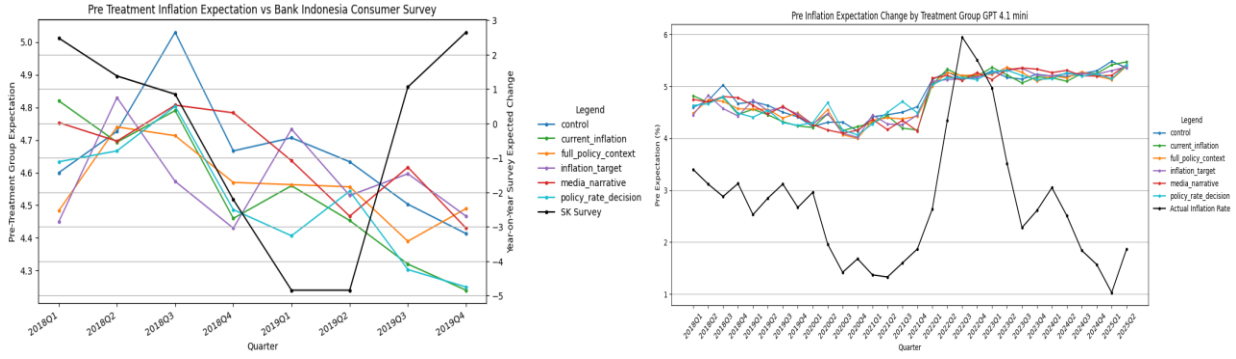
This section presents the main findings from the simulation-based experiment. We begin with the first stage of the survey, asking 30 agents questions about one-year inflation expectation and their reasoning regarding the point prediction. With 32 quarters of observations, we have 5400 different agents to answer the questions and receive treatments. The questions covered (i) a point prediction of the 12-month ahead inflation expectation based on the economic condition in the specific quarter and their demographic characteristic, and (ii) the reason behind that specific number of expectations. Recent studies by Kazinnik (2023) and Fedyk et al. (2024) show that LLMs can mimic human behavior in a financial context. The results align with our hypothesis regarding the utility of LLMs, validating their capacity to simulate the patterns observed in human-based consumer inflation expectation surveys.

The comparative analysis is conducted to examine the effects of agents' attributes on inflation expectation. We use inflation expectation with no additional information as a baseline model and five different treatments, i.e., current inflation information, inflation target, full policy context, media narratives, and policy rate decision. Moreover, we include demographic personas as follows, (i) gender, (ii) age cohort, (iii) education level, (iv) expenditure and income level, (iv) geographical location consist of five different regions in Indonesia, (vi) location (urban/rural), (vii) media exposure, (viii) financial literacy, and (ix) risk appetite. This analysis focuses on the hypothesis that LLMs agents will demonstrate different results of expectation across demographic characteristics.

The simulation reveals that pre-treatment inflation expectations were broadly similar across treatment groups, indicating that the randomization procedure was successful. Figure 2 shows that pre-treatment inflation expectations across all treatment groups are contained within a narrow range between approximately 4.4% and 4.9%. This indicates that prior to treatment, no single group consistently held inflation expectations that were markedly higher or lower than the others. Thus, it suggests a relatively homogenous perception of inflation conditions across the sampled groups. Despite the similarity in levels, the volatility of expectations differs across groups. The inflation target treatment group exhibit comparatively lower variability, reflecting more stable expectation

formation over time. In contrast, current inflation and policy rate decision treatment group display a more pronounced fluctuation, indicating that their expectations may be more sensitive to short-term economic signals. Meanwhile, inflation expectations from the Bank Indonesia household expectation survey exhibit greater volatility over the observed period[2]. This indicates that in the absence of information exposure, experimental respondents exhibit more anchored expectations compared to households in real-world conditions, who are more sensitive to economic shocks or short-term economic shifts. Bank Indonesia household expectation survey suggests that the public's expectations are more reactive and less anchored.

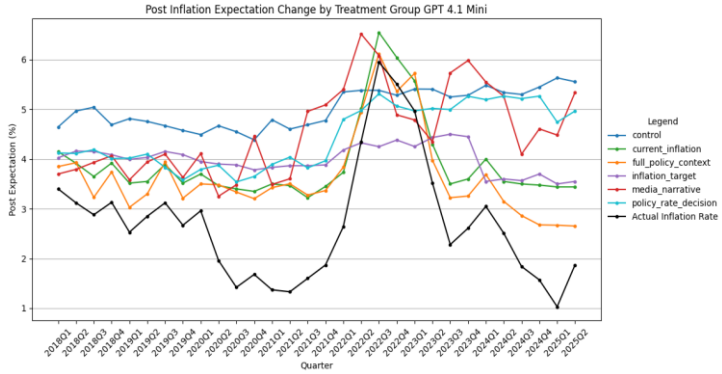
In Figure 2, inflation expectations are closely mirroring the control group and consistently higher than actual inflation but demonstrates a co-movement with the actual inflation rate. This alignment suggests that prior to any intervention, the simulated agents' forecasts are extrapolative. This is consistent with agents' limited information set, echoing findings by Coibion et al. (2018) on household expectations formation. Pre-treatment inflation expectations exhibit temporal variation with a sharp increase from the end of 2021 to the beginning of 2022, coinciding with Indonesia's period of heightened inflationary pressures. However, in late 2023 onward, expectations decreased significantly due to a stable economic outlook, prices of energy and food, and policy interventions after global economic shocks in 2022. We proceed with the second stage of the survey, giving the randomized agents five different treatments to obtain their inflation expectation. The change before and after treatments is treated as a dependent variable in our baseline model to determine the effects of different communication tools on expectations.



Source: Authors calculation

Figure 2 Pre-treatments Inflation Expectation

[2] Bank Indonesia's household inflation expectation survey was discontinued since quarter 1 2020 due to the Covid-19 pandemic.



Source: Authors calculation

Figure 3 Post-treatments Inflation Expectations with GPT

As shown in Figure 3, the post-treatments expectations reveal a distinct divergence in expectations formation and show significantly lower inflation expectations that closely follow the trend of actual inflation. The full policy context treatment produces the most stable inflation expectation, with an average expectation under 4%, except in the shock period. The information treatments utilizing central bank policy communication or technical inflation numbers -namely, full policy context, inflation target, and policy rate decision- produce a more stable trajectory, though the degree of adjustment varies across demographic profiles. In contrast, the media narratives treatment group produces the greatest fluctuations in inflation expectations, indicating that households exposed to news sentiment are more volatile in their responses than the other groups. Meanwhile, the current inflation treatment group tends to imitate extreme movements in the actual inflation rate, consistent with the hypothesis that communicating only the current rate may induce extrapolative expectations (Zarifhonarvar, 2024).

The mean inflation expectation change by treatment group data strongly validates the differential impact of backward-looking versus forward-looking communication strategies. The current inflation and media narratives treatment groups exhibit the greatest volatility, particularly during the 2022 Q3, when the actual inflation rate peaked, producing the largest positive change in expectations. In contrast, the treatment group that was given more focused information on monetary policy signals demonstrated a clear anchoring effect. The inflation target group maintained a remarkably consistent negative deviation, approximately -0.5 to -1.0, throughout the observation period. This suggests that clear communication of the central bank's target provides a stable reference point that encourages simulated agents to moderate their forecasts. The full policy context treatment group proved to be the most effective in moderating post-shock

expectations. Following the 2022 Q4 period, this group's expectation changed to approximately -2.7 in 2025 Q2. Therefore, this indicates that providing a comprehensive explanation of the policy stance leads to significantly lower and more quickly de-anchored expectations relative to the control group. In addition, the absolute change of expectation is higher in the post-pandemic era, indicating the importance of stronger communication during a higher uncertainty period to anchor expectations. This finding suggests that the agent-based framework can reproduce historically salient macroeconomic dynamics similarly to real life.

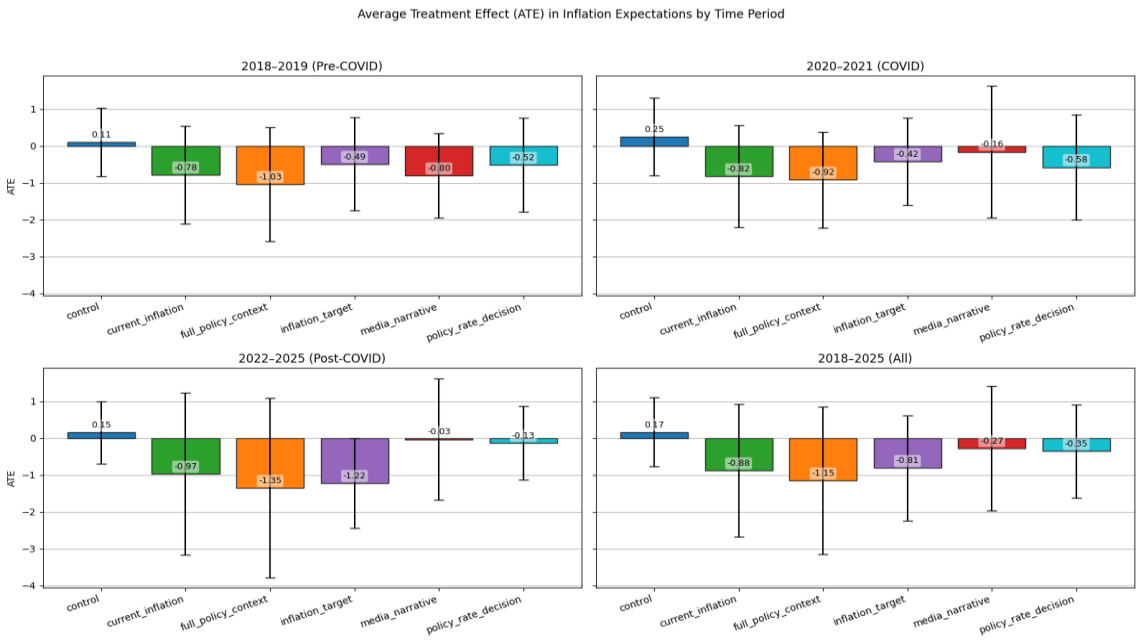
To gain better understanding about the average effect of the treatments on expectation overtime, we calculated the Average Effect Treatment (ATE) with specific period, namely pre-Covid (2018-2019), Covid period (2020-2021), post-Covid (2022-2025) and all periods. ATE calculated as follows:

$$E[(\Delta T_{treatment} - \Delta Y_{control})] \quad (5)$$

Average Treatment Effect (ATE) in inflation expectations offers a quantitative summary of the causal impact of each information treatment relative to the control group across three main distinct economic regimes. Figure 4 presents a time-variant ATE of inflation expectation for each period of interest, where a negative value ATE signifies that the specific treatment is effective in lowering or anchoring inflation expectations. The aggregate results for the entire 2018–2025 period suggest that all policy-related information treatments result in a statistically significant negative ATE, thereby confirming that information treatments successfully lowered simulated expectations compared to the no-information baseline. The full policy context treatment consistently has the largest negative effect, ranging from -0.92 to -1.35. This confirms that a comprehensive communication of the central bank's rationale and stance provides the most robust anchor for simulated household inflation expectations, which aligns with the recommendations for enhanced central bank transparency (Coibion et al., 2018). The impact of treatments also slightly increases over time for most information treatments. Comparing the periods, the negative effects of the current inflation target and full policy context treatments generally become more pronounced in the recent period, indicating that their impact has grown stronger in recent years and suggesting their effectiveness in anchoring inflation expectations. However, policy rate decision treatment consistently has the smallest ATE in all periods, with small and often near-zero, ranging from -0.13 to -0.35. This suggests that merely announcing a policy rate change has the least influence compared to the other treatments.

Further analysis across distinct periods reveals critical heterogeneity in treatment effectiveness. During the high-volatility inflation in the post-COVID period (2022–2025), the magnitude of the negative ATE increased for the most effective anchors. The ATE for the full policy context remained at −1.35, and the inflation target ATE became strongly negative at −1.22. This finding suggests that during the period when actual inflation is high and volatile, a clear communication of the long-term target and the full policy rationale is critical for preventing expectations from becoming de-anchored. In contrast, the ATE for the policy rate decision treatment turns to near zero in the post-COVID period. This large reduction in the policy rate decision treatment indicates that communicating only the interest rate change, without the context of the inflation target or the broader policy strategy, causes the loss of anchoring power during a significant economic shock period. For media narratives treatment, the pre-pandemic effect has a larger coefficient and remained negligible across the latter two periods. These ATE results confirm the high volatility and weak sustained anchoring of this group.

To empirically assess the impact of the treatments on the inflation expectation, we reported the results as shown in Table 4. The regression analysis provides the statistical confirmation of the causal effects inferred from the preceding time-series and ATE analyses, quantifying the impact of the information treatments on the simulated agents' inflation expectations. All the treatments have significantly impacted the expectation change with a negative sign, as expected. This finding confirms that information treatments significantly affect expectations, resulting in a reduction in overestimation. The coefficients for all treatment variables are statistically significant at the 1% level and consistently negative, indicating that the provision of any structured information successfully reduced the agents' overestimation of future inflation relative to the control group. The full policy context treatment has the most elastic and the largest coefficient at 1.32, confirming its superior efficacy in lowering inflation expectations. Meanwhile, the effects of policy rate decision, media narratives, and inflation target treatment are 0.51, 0.44, and 0.99 points, respectively. The media narratives treatment shows the least amount of anchoring effect at 0.438, supporting the previous observation that the information communicated via less formal or uncontrolled channels creates the least effect in anchoring expectations, although still statistically significant. The F-statistic probability is smaller than 0.05, indicating that the model has explanatory power, and all the treatments are jointly explaining changes in inflation expectation among agents. The R-squared and Adjusted R-squared of around 0.23 suggest that the independent variables can moderately explain 23% of the variation in the model.



Source: Authors calculation

Figure 4 Average Treatment Effect for Each Period

Table 4 Regression Results for The Baseline Model GPT – The Treatments

Predictor	Coefficient	Standard Error
Intercept	0.017***	0.027
Treatment: Current Inflation	-1.046***	0.038
Treatment: Inflation Target	-0.978***	0.038
Treatment: Full Policy Context	-1.318***	0.038
Treatment: Media Narratives	-0.438***	0.038
Treatment: Policy Rate Decision	-0.512***	0.038
R-squared	0.235	
Adj. R-squared	0.235	
F-statistic (Prob.)	331.9 (0.000)	
No. Observations	5400	

Source: Author's Calculation. Note: *,**,*** significant in 10%,5%,1% level.

Looking at heterogeneity in Table 5, several demographic and socio-economic factors emerged as statistically significant predictors. This further validates the robustness of the treatment effects. The coefficients for the policy treatments remain virtually unchanged, e.g., Full Policy Context β=−1.324, demonstrating that the causal impact of the information is not confounded by the simulated households' randomized demographic

characteristics. Furthermore, the model provides initial insights into the third research question regarding the heterogeneity of effects. Gender plays a role, with male agents exhibiting slightly higher expectations than female agents, suggesting systematic differences in how information is processed across genders. Urban residency is also a strong predictor with a 0.148 coefficient, suggesting that urban agents report higher inflation expectations compared to rural counterparts, potentially reflecting greater exposure to market prices, media coverage, or information channels. Age had a small and negative effect, implying that younger agents tended to expect slightly higher inflation than older agents. Meanwhile, financial literacy also has a significant impact on household inflation expectations. Financial literacy showed a positive and highly significant association, indicating that agents with better financial knowledge systematically adjust their inflation expectations. This is due to the possibility that a financially literate individual tends to process information more effectively, making them more sensitive to economic signal or outlook, hence, reflecting a greater sensitivity to macroeconomic information or heightened awareness of inflationary risks. The interesting results are that individuals with a senior high school educational level is significantly impact the inflation expectation, but not for bachelor's or master's degree holders. Other socioeconomic variables, such as income, expenditure, risk attitudes, and media exposure, are not statistically significant in this specification.

For further analysis and to evaluate the effects of information treatments on each persona, we conduct the third regression with an interaction term between each demographic characteristic and information treatments, as shown in Table 6. The results are varied across the treatments and demographics. This pattern is consistent with studies from Armantier et al. (2016) and Huber (2023), which conclude that different information treatments can impact inflation across demographics. For instance, a male individual who receives information on the full policy context has the largest coefficient, indicating that providing a complete and clear policy significantly affects expectation formation. This finding is similar to Campbell et al. (2012) who suggest forward guidance with clear signals about future policy paths can effectively shape expectations.

Table 5 Regression Results for The Baseline Model GPT – Demographic Persona

Predictor	Coefficient	Standard Error
Intercept	-0.296*	0.153
Treatment: Current Inflation	-1.050***	0.037
Treatment: Inflation Target	-0.981***	0.037
Treatment: Full Policy Context	-1.324***	0.037
Treatment: Media Narratives	-0.438***	0.037
Treatment: Policy Rate Decision	-0.524***	0.037
Gender: Male	0.064***	0.022
Education: Diploma	0.056	0.048
Education: Master's Degree	-0.062	0.063
Education: Senior High School	-0.093*	0.057
Urban (vs Rural)	0.148***	0.046
Age	-0.002**	0.001
Income	0.078	0.055
Expenditure	0.039	0.051
Financial Literacy	0.049***	0.016
Risk Attitude	0.004	0.006
Media Exposure	0.012	0.051
R-squared	0.268	
Adj. R-squared:	0.266	
F-statistic (Prob.)	123.1 ($p < 0.001$)	
No. Observations	5400	

Source: Author's Calculation. Note: *,**,*** significant in 10%,5%,1% level.

Compared to another treatment, giving individual information about the inflation target does not significantly affect their expectation. This is consistent across all demographic personas, which leads to the conclusion that the inflation target is insufficient to determine their knowledge of future prices. Similarly, providing only policy rate decisions without any further information about the other macroeconomic policies can only impact on the financially literate individual. The significant positive interaction between media exposure and media narratives further confirms that high exposure to general media amplifies the effect of narrative-based information on expectation change. This result, when coupled with the inherently high volatility of the media narratives treatment, poses a challenge to policy-induced stability. However, the education, income, and expenditure are not significantly impacted by any treatments. Which means, any

agent with specific education, income, or expenditure does not change their expectation regarding the treatments.

Table 6 Regression Results with Interaction Terms

Dep: Expectation Change	Current Inflation	Full Policy Context	Inflation Target	Media Narratives	Policy Rate Decision
Intercept	0.915				
Gender - Male	0.036	0.211***	0.111	0.022	0.099
Education - Diploma	-0.031	0.045	0.021	-0.071	-0.024
Education - Master	-0.086	-0.195	0.022	-0.219	-0.140
Education - High School	-0.078	0.110	0.083	0.179	-0.014
Location - Urban	0.123	0.143	-0.107	-0.174	-0.139
Age	-0.001	-0.002	0.000	0.005*	0.003
Income	0.304	0.124	0.269	-0.003	0.045
Expenditure	-0.088	-0.030	-0.037	0.053	0.105
Financial Literacy	0.103*	0.179***	0.061	0.096*	0.110**
Media Exposure	0.043	0.040	0.048	0.120*	0.078
Risk Attitude	0.017	0.017	0.010	0.002	-0.005
R-sqr	0.288				
Adj. R-sqr	0.278				
F-stat (prob.)	30.31 (0.000)				
Durbin-Watson Stat	1.623				

Source: Author's calculation. i) *,**,*** significant in α = 10%,5%,1%. (ii) interaction model is the fixed effect model to control the effect of demographic persona. All regression results presented in Appendix 2.

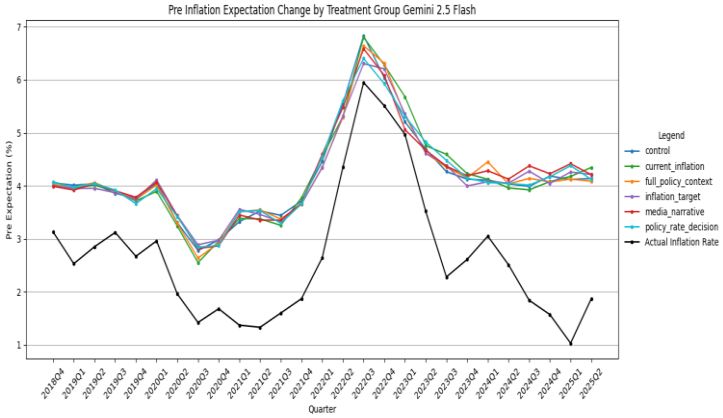
All the aforementioned results provide robust evidence that the causal impact of the information treatments is heterogeneous, underscoring the necessity of segmenting communication strategies based on demographic and literacy profiles. Based on the findings, the full policy context information is needed to influence households' inflation expectations, although from the regression results, it only impacts individuals with a specific gender and financial literacy level. However, surveys with AI agents perform more consistent and predictable reactions for information treatments and may overlook the bias and sometimes irrational ways in which humans process the information (Coibion et al., 2022; Weber et al., 2022).

As mentioned in Zarifhonarvar (2024), AI agent-based surveys are crucial not only for enhancing AI-driven forecasting tools but also for refining how central banks communicate and frame their policy strategies. Given our findings, it suggests that AI can provide valuable information and tools for predicting the impact of some information on public inflation expectations. This also leads to a major recommendation for central

bank policy, that central bank communication should be delivered with direct, clear, and consistent messages to anchor inflation expectations, especially for households.

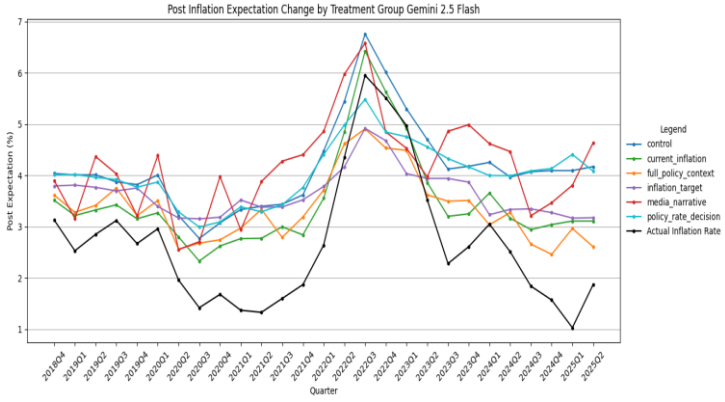
IV.2 Robustness Check and Discussion

Building on the previous findings using GPT, we also conducted a robustness check with other LLMs, Gemini 2.5 flash, to make sure that the agents are normally distributed and randomly assigned for each treatment. For the first robustness check, we compare the pre- and post-treatment using graphical analysis. As shown in Figure 5 and Figure 6, the pre- and post-treatment using Gemini gives similar results with the GPT model. The agents' inflation expectation using Gemini is also consistently higher than the actual inflation. The absolute change of expectation is larger in the post-pandemic era, indicating the importance of stronger communication during a higher uncertainty period to anchor expectations.



Source: Author's Calculation

Figure 5 Post-treatments Inflation Expectation with Gemini



Source: Author's Calculation

Figure 6 Post-treatments Inflation Expectation with Gemini

Policy rate decision treatment results in the most similar trend with the actual inflation, and the average expectation is consistently under 4%, except in those shocks period. The standard deviation with Gemini is relatively small, 0.6, compared to the actual inflation standard deviation of 1.2. Nevertheless, this deviation is higher than our baseline model using GPT, suggesting that Gemini's agents' inflation expectation may acquire more volatility than GPT's. Table 6 presents the results of another way to do a robustness check, by modelling the effect of treatments on inflation expectation change. We utilized Equation (1) to Equation (3) to estimate the impact of the treatments, as well as the heterogeneity across the demographic characteristics and the interaction between them. The results imply a similar finding and robust coefficient to those from GPT. Information treatments significantly affect expectations, especially for the full policy context with coefficients around 0.79 points, followed by current inflation, inflation target, and policy rate decision. However, the model produces a small and unsignificant media narratives effect on expectation, unlike the GPT. The R-squared and Adjusted R-squared are also relatively smaller, although the F-statistic is still significant. Moving to the heterogeneity test, we can see in Table 7 that gender, location, age, and financial literacy significantly impact change in inflation expectation. This conclusion is identical to the results from GPT.

Table 7 Regression Results for The Baseline Model Gemini – The Treatments

Predictor	Coefficient	Standard Error
Intercept	0.014***	0.027
Treatment: Current Inflation	-0.697***	0.038
Treatment: Inflation Target	-0.789***	0.038
Treatment: Full Policy Context	-0.546***	0.038
Treatment: Media Narratives	-0.014	0.038
Treatment: Policy Rate Decision	-0.126***	0.038
R-squared	0.149	
Adj. R-squared	0.148	
F-statistic (Prob.)	170.2 ($p < 0.001$)	
No. Observations	4860	

Source: Author's Calculation. Note: *,**,*** significant in 10%,5%,1% level.

Notwithstanding the magnitude of the coefficients, estimation based on the Gemini model is robust and provides the same results as GPT, shown in Table 8. The model also gives us a consistent conclusion for the effect of treatments, different personas and characteristics, and robustness over time. We can conclude that the strong consistency observed between these two LLMs to produce AI agents has significant implications regarding the reliability of AI agents-based in mimicking human-based surveys. This reliability enhances the potential of LLMs as tools in the broader economic research field, as stated by Zarifhonarvar (2024).

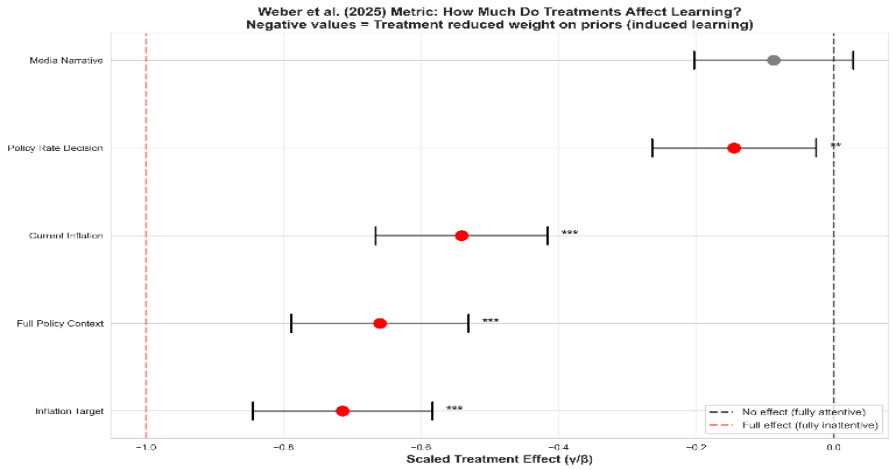
Table 8 Regression Results for The Baseline Model Gemini – Demographic Persona

Predictor	Coefficient	Standard Error
Intercept	-1.355*	0.348
Treatment: Current Inflation	-0.699***	0.038
Treatment: Inflation Target	-0.504***	0.038
Treatment: Full Policy Context	-0.793***	0.038
Treatment: Media Narratives	-0.010***	0.038
Treatment: Policy Rate Decision	-0.128***	0.038
Gender: Male	0.062***	0.022
Education: Diploma	0.043	0.049
Education: Master's Degree	-0.028	0.065
Education: Senior High School	-0.109*	0.061
Urban (vs Rural)	0.130***	0.048
Age	-0.0004**	0.001
Income	-0.011	0.057
Expenditure	0.081	0.052
Financial Literacy	0.047***	0.016
Risk Attitude	-0.002	0.006
Media Exposure	0.003	0.018
R-squared	0.170	
Adj. R-squared:	0.170	
F-statistic (Prob.)	65.7 (0.001)	
No. Observations	4860	

Source: Author's Calculation. Note: *,**,*** significant in 10%,5%,1% level.

IV. 3 Bayesian Learning

Following Weber et al. (2025) scaled treatment effect metric (γ/β), we measure how much each information treatment induced learning by shifting respondents away from their prior beliefs. The scale runs from 0 (fully attentive baseline, meaning no learning induced because respondents were already incorporating the information) to -1 (fully inattentive, meaning maximum learning induced). Figure 7 shows that Inflation Target and Full Policy Context treatments produced the strongest learning effects at around -0.7 and -0.6, respectively, followed by Current Inflation at around -0.55. This suggests that respondents were most inattentive to—and thus learned most from—explicit communication about targets and policy frameworks. Policy Rate Decision had a smaller but still significant effect (around -0.15), while Media Narratives treatment showed no statistically significant effect (grey dot, confidence interval crossing zero), indicating that narrative-style media framing did not meaningfully shift respondents' weight on priors. This pattern suggests that direct, institutional information about monetary policy fundamentals is more effective at updating inflation expectations than media-mediated narratives.



Source: Author's Calculation

Figure 7 Scaled Treatment Effect using Weber et. al (2025) Metric

IV. 4 Reasoning Behind Response

To complement the quantitative results, a textual reasoning analysis is conducted to assess how agents reasoned their inflation expectations prior to and after receiving different informational treatments. Using automated text classification techniques, the analysis identifies the main economic concepts that recurred in the reasoning text, e.g., inflation, policy, currency, wages, saving behavior, and measures how their frequencies

shift across treatments. Other linguistic indicators, such as reasoning length and certainty expressions, are also evaluated.

Each information treatment triggers distinct cognitive frames in how simulated household agents reasoned about their inflation expectations. Households receiving a full policy context treatment yielded a balanced and integrative reasoning to their expectation, as shown in Table 9. Both policy awareness and currency mention rose moderately, and reasoning length increased by around 10% compared to pre-treatment. This result indicates richer and more elaborate thoughts when agents form their expectations.

Table 9 Sample of Reasoning Analysis for Full Policy Context Treatment

Concept	Pre %	Post %	Change
Currency	5.6%	40.6%	+35.0%
Personal experience	88.3%	60.6%	-27.8%
Global factors	95.3%	71.8%	-23.6%
Policy awareness	87.8%	95.2%	+7.4%
Wage concern	8.4%	1.9%	-6.6%
Supply chain	26.8%	30.3%	+3.6%
Savings behavior	0.6%	2.7%	+2.1%
Consumer behavior	2.3%	3.7%	+1.3%
Inflation awareness	100.0%	100.0%	+0.0%

Source: Author's Calculation

Further discussion referring to Table 10 shows that the household receiving policy rate decision treatment induced a strong behavioural reasoning, as indicated by the increase in the mention of savings behaviour (+81 pp) and consumer behaviour (+42 pp), which became dominant. This result shows that agents translated policy signals into a household-level financial logic. On the other hand, media narratives treatment caused the most significant change in the reframing agents' expectations. After receiving media narratives treatment, the mentions of currency surged (+86 pp), while the mentions of policy awareness collapsed (-75 pp). This suggests that agents shifted from institutional reasoning toward exchange rate-driven interpretations. Meanwhile, inflation target treatment narrowed the reasoning scope as the mention of global factors declines (-19 pp) and responses become shorter (–70 characters). This result suggests a simplified, rule-based reasoning anchored on the target itself. This case also applies to the current inflation treatment. However, all treatments reduced the frequency of personal or

anecdotal reasoning, which remained stable only in the control group. The largest decline of personal or anecdotal reasoning occurred under policy rate decision treatment (–47 pp), implying that actionable policy information effectively redirected agents away from the observational and experiential thinking toward an analytical and institutional reasoning.

Table 10 Summary of information treatment groups

Concept/Treatment	control	full policy context	current inflation	media narrative	policy rate	inflation target
	Absolute Change					
savings_behavior	0.4	2.1	0.7	0.4	80.8	0.3
personal_experience	0.6	27.8	21.0	36.1	46.8	9.8
consumer_behavior	0.9	1.3	0.0	1.1	41.9	2.2
supply_chain	4.9	3.6	9.1	8.6	14.6	10.3
policy_awareness	7.7	7.4	17.9	75.2	14.1	12.9
wage_concern	11.3	6.6	0.9	6.8	7.3	3.9
currency	0.3	35.0	2.3	86.3	5.9	1.6
global_factors	1.6	23.6	1.3	3.1	1.3	19.1
employment	0.1	0.0	0.0	0.1	0.1	0.2
inflation_awareness	0.0	0.0	0.0	0.0	0.0	0.0

Source: Author's Calculation.

Reasoning length analysis suggests that changes in reasoning length varied by treatment. Table 11 shows full policy context treatment induced an expanded reasoning from agents (+34 chars), and a similar case was found in policy rate decision treatment, where reasoning expanded (+11 chars). In contrast, the inflation target and media narrative treatment induced a more compressed reasoning for agents' expectations, around 69 characters and 21 characters, respectively. This pattern indicates that complex, multi-dimensional information encourages elaboration. While highly focused messages promote cognitive compression, agents settle on concise explanations once a clear interpretive anchor is provided. Across all treatments, certainty expressions ("definitely," "will," "must") remained rare (<1%), while hedging language ("might," "could," "I think," "however") dominated at around 98% pre and post. This suggests that information treatments changed what agents reasoned about, but not how confidently they expressed those beliefs. The LLM agents maintained consistent epistemic caution throughout, reflecting linguistic humility similar to human reasoning patterns under uncertainty.

Table 11 Summary of Length Analysis

Treatment	Pre Avg Length	Post Avg Length	Change
Control	353 chars	355 chars	+2 chars
Full policy context	350 chars	384 chars	+34 chars
Current inflation	355 chars	356 chars	+2 chars
Media narrative	353 chars	332 chars	-21 chars
Policy rate decision	354 chars	365 chars	+11 chars
Inflation target	350 chars	281 chars	-69 chars

Source: Author's Calculation. "Chars" refer to characters typed for each treatment

Overall, the treatments reshaped reasoning content more than reasoning confidence. Information exposure produced cognitive reframing—not a stronger conviction. Media narrative and policy-related treatments redirected the agent analysis to focus on currency and savings behaviour. While abstract signals like inflation targets compressed reasoning into simpler mental models. The results indicate that policy communication's influence lies in changing interpretive frameworks, but not necessarily in increasing confidence.

The textual reasoning analysis demonstrates that information treatments achieved cognitive reframing without altering the certainty of beliefs. Agents' key element of reasoning shifts was different between treatments. The policy rate decision treatment encouraged strong movement towards a behavioral interpretation, while media narratives treatment encouraged agents to move away from the policy perspective for a strongly currency-driven understanding. In the analysis of reasoning length, it became evident that complex information, such as full policy context treatment, produced elaboration. While simplifying signals, such as in the inflation target treatment, produced cognitive compression. The significant finding here is that the certainty language patterns remained consistently dominated by hedging expressions, confirming that the treatments changed the agents' interpretive framework, but not their conviction (Hansen et al., 2024). Ultimately, the full policy context treatment proved to be unique in yielding a balanced and integrative reasoning style, producing a richer elaboration of economic thought, which included cognizance of both the policy and currency concepts.

V. Conclusion

This study provides a valuable contribution to our understanding of the formation of household inflation expectations in Indonesia while also addressing the potential role that generative AI may play in replicating this kind of behavioral process. The results show that the use of LLMs can simulate 5,400 synthetic household personas across demographic and geographic variation, which provides a scalable alternative to traditional surveys. This method enables a controlled experimental environment to examine how different modalities of information processes, such as central bank communication and media narratives, may affect inflation expectations. The experiment expands existing evidence from Coibion et al. (2019, 2020a, 2020b) and Weber et al. (2022), which show that structurally well-communicated policy can provide better anchoring for inflation expectations, even in synthetic groups. Our findings suggest that a full policy context has the greatest anchoring potential, followed by the communication of inflation targeting. This is consistent with Bank Indonesia's strategy to enhance credibility through clear and unambiguous channels of communication.

The key findings show several important patterns. *First*, information provision substantially reduces the overestimation of inflation, particularly information that contains the full policy context, current inflation, and the inflation target. This suggests that anchoring of expectations is feasible through clear communication and a complete context. *Second*, the heterogeneity tests indicate that urban, male agents, and those with good financial literacy are more responsive to information treatments. This shows a heterogeneous processing of information with respect to characteristics of demographic groups consistent with D'Acunto et al. (2019) and Jiang et al. (2024). *Third*, a comparison of the simulations based on GPT and those based on Gemini indicates robustness, as both models yield similar directional effects and time effects. These findings indicate the robustness of generative models in capturing structured behavior responses, as well as their applicability to policy experimentation in an environment where survey data are lacking or expensive to obtain. In addition, Bayesian learning analysis suggests that agents were most attentive to explicit communication about targets and policy frameworks, rather than the effect of inflation target or policy rate only.

This experiment corroborates Akata et al. (2023), Brookins and DeBacker (2023), and Hansen et al. (2024) that LLM agents can emulate key aspects of human reasoning in repeated decision or strategic contexts with respect to the model's ability to replicate human behavior. However, there are important caveats to the simulation. LLM's display

a certain degree of rationality and coherence beyond that of the human respondents but lack emotional salience and contextual bias. As emphasized by Raman et al. (2024) and Horton (2023), these models demonstrate bounded rationality—where models can mirror aggregate behavioral patterns, but not the subjective uncertainty or sentiment-driven deviations which are typical for real households. The "reasoning" that lies behind certain inflation expectations reflects a probabilistic recourse to textual patterns rather than any genuine cognitive processes where the cognitive processes leading to expectation formation are considered and dealt with. This is consistent with the view of Korinek (2023) that AI in economics should be construed as a complement to, rather than a substitute for, human reasoning and the institutional context in which the reasoning takes place.

In conclusion, this study demonstrates that AI-driven agent simulations can complement central bank tools for monitoring and analyzing inflation expectations, especially in data-scarce environments like Indonesia. The results validate the feasibility of using LLMs as experimental instruments for testing communication strategies and expectation anchoring mechanisms. Moreover, the findings state that prior inflation expectations appear insensitive to the state of the economy, which is not in accordance with Weber et al. (2025). Their study finds that the economic environment affects how agents learn from new information, both in low and high regimes of inflation in advanced economies. The explanation behind this finding is that the LLMs may not successfully capture the time variation. Nevertheless, future research should pursue hybrid frameworks that integrate LLM-based simulations with human survey data and high-frequency behavioral indicators (e.g., social media sentiment or transaction-level data, as suggested by Denes et al., 2021; Shcherbakov & Karpov, 2024). Continuous model refinement, multi-model comparisons, and interpretability enhancements are essential to ensure that AI-based approaches remain transparent, contextually relevant, and aligned with economic theory. In doing so, generative AI may evolve into a robust analytical companion for central banks—advancing both understanding and management of inflation expectations in an increasingly information-driven economy.

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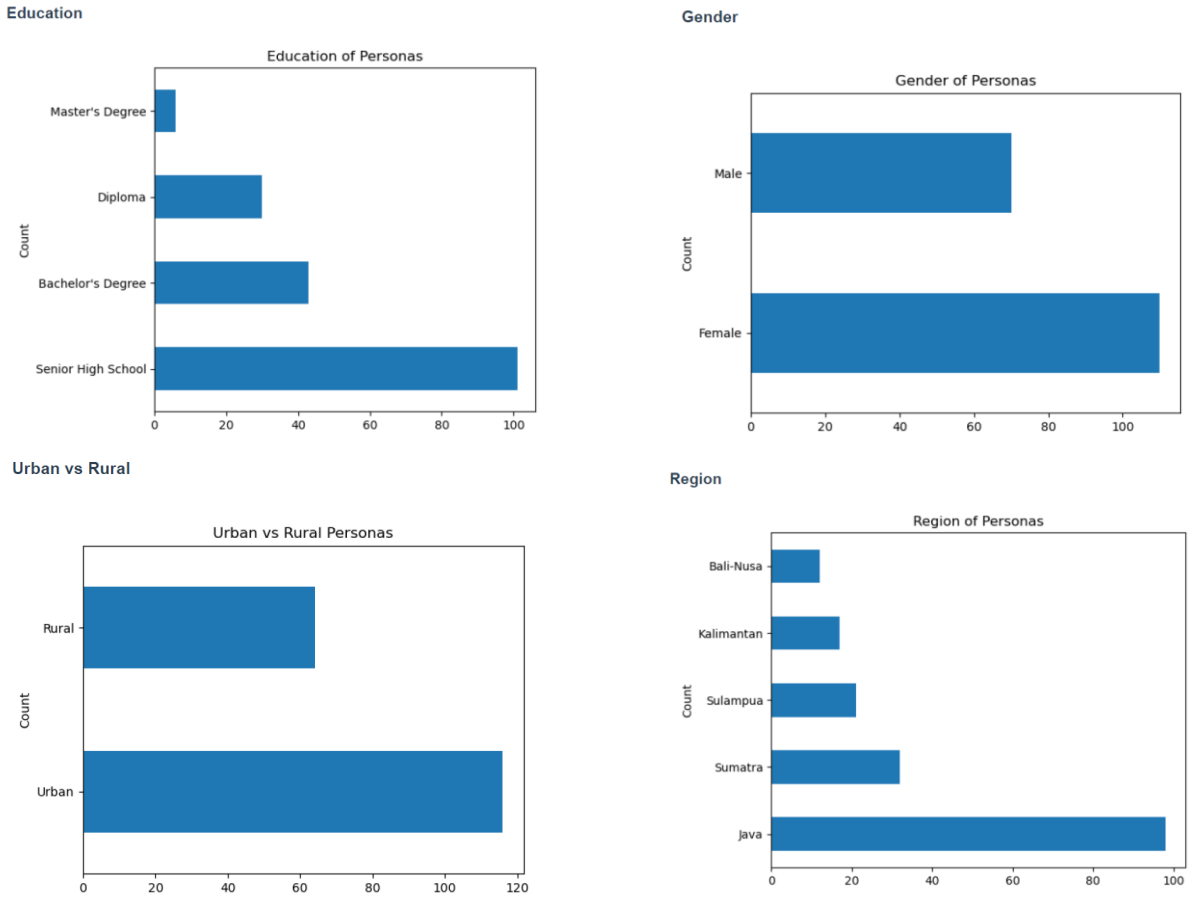
APPENDIX 1. PERSONA CHARACTERISTICS

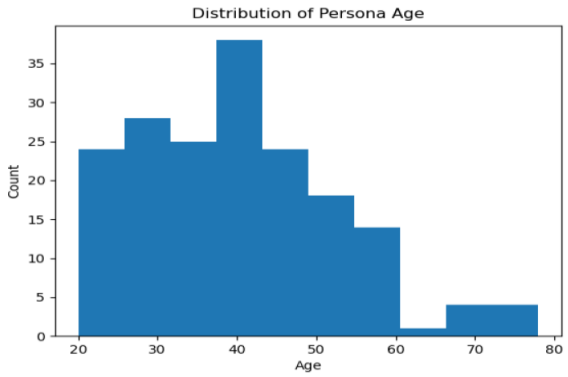
A. Persona's Count



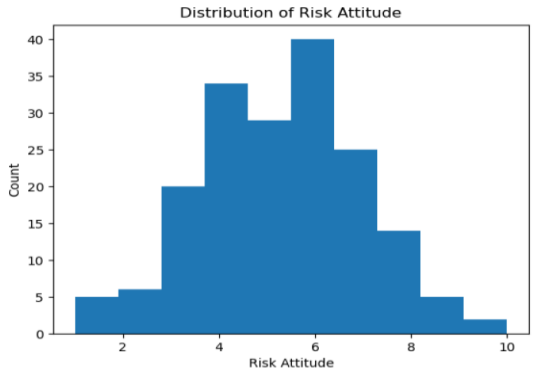
Appendix 1A. Number of Persona Created by Demographic Characteristics

B. Persona's Distribution

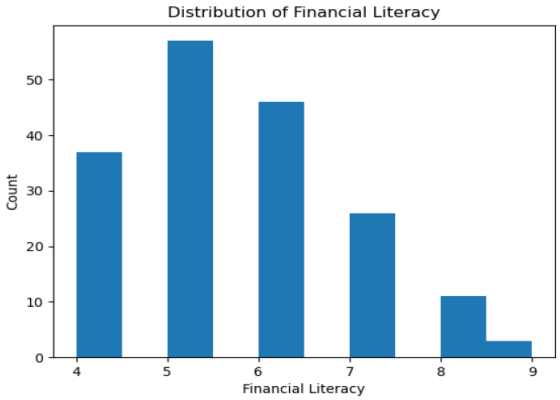
Age



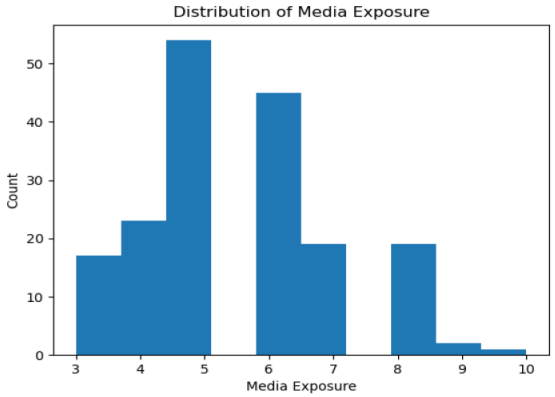
Risk Preference



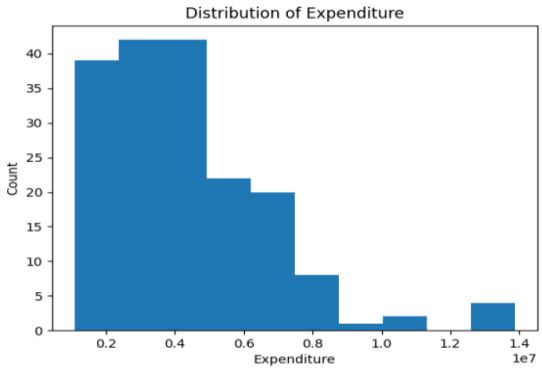
Financial Literacy



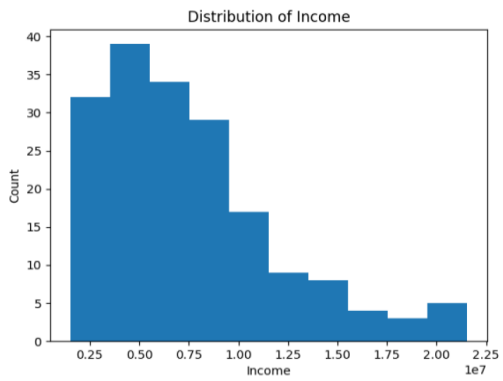
Media Exposure



Expenditure



Income

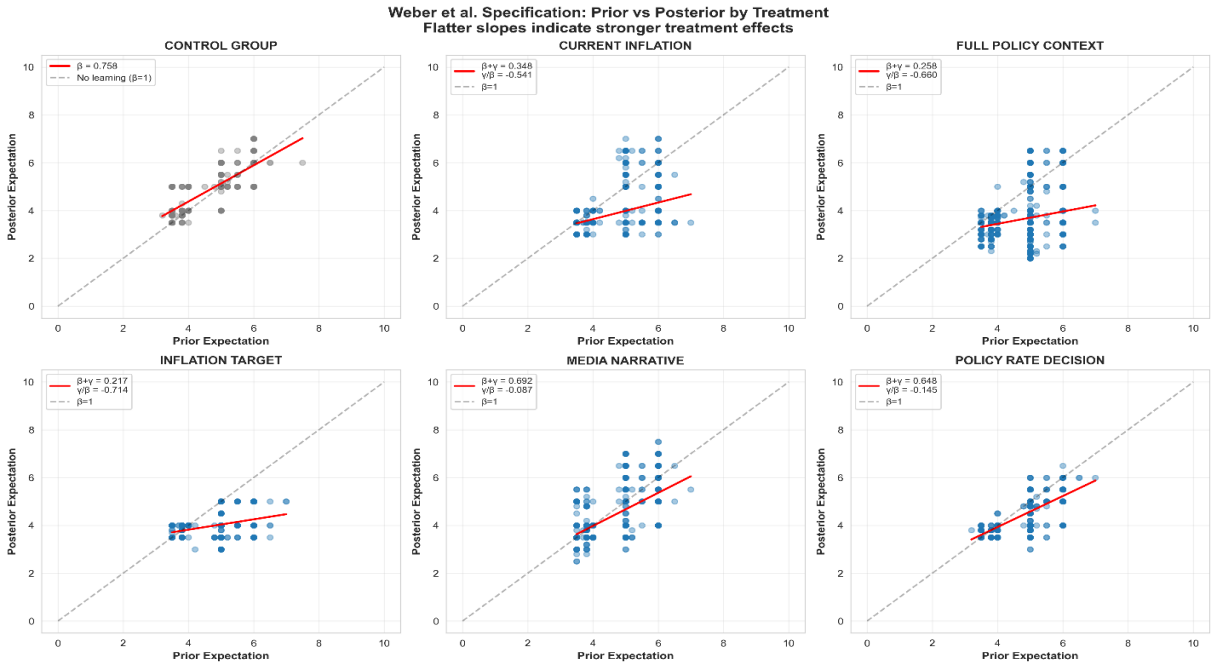


Appendix 1B. Distribution of Persona Created by Demographic Characteristics Per Quarter

APPENDIX 2. COMPLETE FIXED-EFFECT MODEL REGRESSION

Variable	Coef.	Std.Err.	t	P>|t|
Intercept	0.915	0.839	1.090	0.276
C(treatment_group)[T.current_inflation]	-5.355	1.172	-4.567	0.000
C(treatment_group)[T.full_policy_context]	-4.258	1.170	-3.638	0.000
C(treatment_group)[T.inflation_target]	-5.308	1.173	-4.526	0.000
C(treatment_group)[T.media_narrative]	-2.569	1.180	-2.177	0.030
C(treatment_group)[T.policy_rate_decision]	-3.857	1.173	-3.287	0.001
C(gender)[T.Male]	-0.024	0.054	-0.445	0.656
C(education)[T.Diploma]	-0.029	0.118	-0.243	0.808
C(education)[T.Master's Degree]	0.042	0.145	0.292	0.770
C(education)[T.Senior High School]	-0.117	0.143	-0.815	0.415
C(urban_rural)[T.Urban]	0.152	0.114	1.340	0.180
C(treatment_group)[T.current_inflation]:C(gender)[T.Male]	0.036	0.075	0.483	0.629
C(treatment_group)[T.full_policy_context]:C(gender)[T.Male]	0.211	0.076	2.785	0.005
C(treatment_group)[T.inflation_target]:C(gender)[T.Male]	0.111	0.076	1.465	0.143
C(treatment_group)[T.media_narrative]:C(gender)[T.Male]	0.022	0.076	0.291	0.771
C(treatment_group)[T.policy_rate_decision]:C(gender)[T.Male]	0.099	0.075	1.307	0.191
C(treatment_group)[T.current_inflation]:C(education)[T.Diploma]	-0.031	0.166	-0.188	0.851
C(treatment_group)[T.full_policy_context]:C(education)[T.Diploma]	0.045	0.169	0.267	0.790
C(treatment_group)[T.inflation_target]:C(education)[T.Diploma]	0.021	0.162	0.130	0.896
C(treatment_group)[T.media_narrative]:C(education)[T.Diploma]	-0.071	0.168	-0.420	0.674
C(treatment_group)[T.policy_rate_decision]:C(education)[T.Diploma]	-0.024	0.166	-0.143	0.886
C(treatment_group)[T.current_inflation]:C(education)[T.Master's Degree]	-0.086	0.218	-0.394	0.694
C(treatment_group)[T.full_policy_context]:C(education)[T.Master's Degree]	-0.195	0.205	-0.951	0.342
C(treatment_group)[T.inflation_target]:C(education)[T.Master's Degree]	0.022	0.219	0.099	0.921
C(treatment_group)[T.media_narrative]:C(education)[T.Master's Degree]	-0.219	0.220	-0.997	0.319
C(treatment_group)[T.policy_rate_decision]:C(education)[T.Master's Degree]	-0.140	0.210	-0.667	0.505
C(treatment_group)[T.current_inflation]:C(education)[T.Senior High School]	-0.078	0.203	-0.384	0.701
C(treatment_group)[T.full_policy_context]:C(education)[T.Senior High School]	0.110	0.203	0.544	0.587
C(treatment_group)[T.inflation_target]:C(education)[T.Senior High School]	0.083	0.203	0.412	0.681
C(treatment_group)[T.media_narrative]:C(education)[T.Senior High School]	0.179	0.206	0.865	0.387
C(treatment_group)[T.policy_rate_decision]:C(education)[T.Senior High School]	-0.014	0.202	-0.069	0.945
C(treatment_group)[T.current_inflation]:C(urban_rural)[T.Urban]	0.122	0.163	0.746	0.455
C(treatment_group)[T.full_policy_context]:C(urban_rural)[T.Urban]	0.143	0.163	0.876	0.381
C(treatment_group)[T.inflation_target]:C(urban_rural)[T.Urban]	-0.107	0.162	-0.657	0.511
C(treatment_group)[T.media_narrative]:C(urban_rural)[T.Urban]	-0.174	0.164	-1.064	0.288
C(treatment_group)[T.policy_rate_decision]:C(urban_rural)[T.Urban]	-0.139	0.162	-0.860	0.390
age	-0.003	0.002	-1.548	0.122
C(treatment_group)[T.current_inflation]:age	-0.001	0.003	-0.183	0.855
C(treatment_group)[T.full_policy_context]:age	-0.002	0.003	-0.620	0.535
C(treatment_group)[T.inflation_target]:age	0.000	0.003	0.089	0.929
C(treatment_group)[T.media_narrative]:age	0.005	0.003	1.744	0.081
C(treatment_group)[T.policy_rate_decision]:age	0.003	0.003	0.943	0.346
np.log(income)	-0.058	0.138	-0.419	0.675
C(treatment_group)[T.current_inflation]:np.log(income)	0.304	0.194	1.564	0.118
C(treatment_group)[T.full_policy_context]:np.log(income)	0.124	0.195	0.634	0.526
C(treatment_group)[T.inflation_target]:np.log(income)	0.269	0.193	1.399	0.162
C(treatment_group)[T.media_narrative]:np.log(income)	-0.003	0.195	-0.017	0.987
C(treatment_group)[T.policy_rate_decision]:np.log(income)	0.045	0.189	0.238	0.812
np.log(expenditure)	0.050	0.126	0.397	0.692
C(treatment_group)[T.current_inflation]:np.log(expenditure)	-0.088	0.177	-0.497	0.619
C(treatment_group)[T.full_policy_context]:np.log(expenditure)	-0.030	0.179	-0.166	0.868
C(treatment_group)[T.inflation_target]:np.log(expenditure)	-0.037	0.177	-0.208	0.835
C(treatment_group)[T.media_narrative]:np.log(expenditure)	0.053	0.177	0.297	0.766
C(treatment_group)[T.policy_rate_decision]:np.log(expenditure)	0.105	0.171	0.612	0.540
financial_literacy	-0.043	0.039	-1.112	0.266
C(treatment_group)[T.current_inflation]:financial_literacy	0.103	0.055	1.864	0.062
C(treatment_group)[T.full_policy_context]:financial_literacy	0.179	0.055	3.279	0.001
C(treatment_group)[T.inflation_target]:financial_literacy	0.061	0.055	1.110	0.267
C(treatment_group)[T.media_narrative]:financial_literacy	0.096	0.055	1.741	0.082
C(treatment_group)[T.policy_rate_decision]:financial_literacy	0.110	0.055	2.014	0.044
media_exposure	-0.044	0.041	-1.076	0.282
C(treatment_group)[T.current_inflation]:media_exposure	0.043	0.059	0.725	0.469
C(treatment_group)[T.full_policy_context]:media_exposure	0.040	0.059	0.673	0.501
C(treatment_group)[T.inflation_target]:media_exposure	0.048	0.060	0.798	0.425
C(treatment_group)[T.media_narrative]:media_exposure	0.120	0.060	1.994	0.046
C(treatment_group)[T.policy_rate_decision]:media_exposure	0.078	0.059	1.331	0.183
risk_attitude	-0.002	0.014	-0.111	0.911
C(treatment_group)[T.current_inflation]:risk_attitude	0.017	0.021	0.835	0.404
C(treatment_group)[T.full_policy_context]:risk_attitude	0.017	0.020	0.830	0.407
C(treatment_group)[T.inflation_target]:risk_attitude	0.010	0.020	0.476	0.634
C(treatment_group)[T.media_narrative]:risk_attitude	0.002	0.020	0.115	0.909
C(treatment_group)[T.policy_rate_decision]:risk_attitude	-0.005	0.020	-0.268	0.788

APPENDIX 3. BAYESIAN LEARNING WITH INTERACTION TERM



APPENDIX 4. PRE VS POST TREATMENT REASONING ANALYSIS

A. Key Concept Shifts by Information Treatment Group

CONTROL (n=900)

Concept	Pre %	Post %	Change
Wage_concern	6.10%	17.40%	**11.30%**
Policy_awareness	85.10%	92.80%	**7.70%**
Supply_chain	26.70%	21.80%	-4.90%
Global_factors	94.00%	92.40%	-1.60%
Consumer_behavior	1.80%	2.70%	**0.90%**
Personal_experience	87.40%	88.00%	**0.60%**
Savings_behavior	0.20%	0.70%	**0.40%**
Currency	6.10%	6.40%	**0.30%**
Employment	0.10%	0.20%	**0.10%**
Inflation_awareness	100.00%	100.00%	0.00%

FULL_POLICY_CONTEXT (n=900)

Concept	Pre %	Post %	Change
Currency	5.60%	40.60%	**35.00%**
Personal_experience	88.30%	60.60%	-27.80%
Global_factors	95.30%	71.80%	-23.60%
Policy_awareness	87.80%	95.20%	**7.40%**
Wage_concern	8.40%	1.90%	-6.60%
Supply_chain	26.80%	30.30%	**3.60%**
Savings_behavior	0.60%	2.70%	**2.10%**
Consumer_behavior	2.30%	3.70%	**1.30%**
Inflation_awareness	100.00%	100.00%	0.00%

CURRENT_INFLATION (n=900)

Concept	Pre %	Post %	Change
Personal_experience	87.30%	66.30%	-21.00%
Policy_awareness	87.20%	69.30%	-17.90%
Supply_chain	26.70%	17.60%	-9.10%
Currency	5.90%	3.60%	-2.30%
Global_factors	93.10%	91.80%	-1.30%
Wage_concern	10.20%	9.30%	-0.90%
Savings_behavior	0.80%	1.40%	**0.70%**
Inflation_awareness	100.00%	100.00%	0.00%
Consumer_behavior	3.30%	3.30%	0.00%

MEDIA_NARRATIVE (n=900)

Concept	Pre %	Post %	Change
Currency	6.40%	92.80%	**86.30%**
Policy_awareness	85.20%	10.00%	-75.20%
Personal_experience	88.40%	52.30%	-36.10%
Supply_chain	26.20%	34.80%	**8.60%**
Wage_concern	8.70%	1.90%	-6.80%
Global_factors	94.30%	91.20%	-3.10%
Consumer_behavior	2.n kata70%	1.60%	-1.10%

Concept	Pre %	Post %	Change
Savings_behavior	0.90%	0.40%	-0.40%
Employment	0.00%	0.10%	**0.10%**
Inflation_awareness	100.00%	100.00%	0.00%

POLICY_RATE_DECISION (n=900)

Concept	Pre %	Post %	Change
Savings_behavior	0.30%	81.10%	**80.80%**
Personal_experience	89.10%	42.30%	-46.80%
Consumer_behavior	3.10%	45.00%	**41.90%**
Supply_chain	29.70%	15.10%	-14.60%
Policy_awareness	85.90%	100.00%	**14.10%**
Wage_concern	9.00%	1.70%	-7.30%
Currency	6.80%	0.90%	-5.90%
Global_factors	94.20%	92.90%	-1.30%
Employment	0.20%	0.10%	-0.10%
Inflation_awareness	100.00%	100.00%	0.00%

INFLATION_TARGET (n=900)

Concept	Pre %	Post %	Change
Global_factors	93.80%	74.70%	-19.10%
Policy_awareness	86.70%	99.60%	**12.90%**
Supply_chain	28.60%	18.20%	-10.30%
Personal_experience	88.90%	79.10%	-9.80%
Wage_concern	8.00%	4.10%	-3.90%
Consumer_behavior	2.80%	0.60%	-2.20%
Currency	3.20%	1.70%	-1.60%
Savings_behavior	0.30%	0.00%	-0.30%
Employment	0.20%	0.00%	-0.20%
Inflation_awareness	100.00%	100.00%	0.00%

B. Reasoning Length Analysis by Information Treatment Group

Treatment	Pre Avg Length	Post Avg length	Change
Control	353 chars	355 chars	**+2 chars**
Full_policy_context	350 chars	384 chars	**+34 chars**
Current_inflation	355 chars	356 chars	**+2 chars**
Media_narrative	353 chars	332 chars	-21 chars
Policy_rate_decision	354 chars	365 chars	**+11 chars**
Inflation_target	350 chars	281 chars	-69 chars

C. Certainty Language Patterns by Information Treatment Group

CONTROL

Certainty Level	Pre %	Post %	Change
High	0.10%	0.10%	0.00%
Medium	0.10%	0.10%	0.00%
Low	0.10%	0.10%	0.00%
Hedging	98.20%	97.20%	-1.00%

FULL_POLICY_CONTEXT

Certainty Level	Pre %	Post %	Change
High	0.10%	0.10%	0.00%
Medium	0.10%	0.10%	0.00%
Low	0.10%	0.10%	0.00%
Hedging	98.30%	95.70%	-2.70%

CURRENT_INFLATION

Certainty Level	Pre %	Post %	Change
High	0.10%	0.10%	0.00%
Medium	0.10%	0.10%	0.00%
Low	0.10%	0.10%	0.00%
Hedging	98.10%	93.90%	-4.20%

MEDIA_NARRATIVE

Certainty Level	Pre %	Post %	Change
High	0.10%	0.10%	0.00%
Medium	0.10%	0.10%	0.00%
Low	0.10%	0.10%	0.00%
Hedging	97.90%	87.60%	-10.30%

POLICY_RATE_DECISION

Certainty Level	Pre %	Post %	Change
High	0.10%	0.10%	0.00%
Medium	0.10%	0.10%	0.00%
Low	0.10%	0.10%	0.00%
Hedging	98.10%	97.30%	-0.80%

INFLATION_TARGET

Certainty Level	Pre %	Post %	Change
High	0.10%	0.10%	0.00%
Medium	0.10%	0.10%	0.00%
Low	0.10%	0.10%	0.00%
Hedging	98.10%	99.10%	**1.00%**