Integrating Fine-Tuned GPT with Agent-Based Economic Modeling for Transparent Wage Policy Decisions

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***Abstract*—This study presents a decision-support system powered by GPT-enhanced insights to help policymakers explore the economic effects of minimum wage policies in the Philippines. The system integrates agent-based simulation, fuzzy logic, reinforcement learning, and Fuzzy Analytic Hierarchy Process (Fuzzy AHP) to model the complex relationships between wages, inflation, firm behavior, and employment. At its core is a fine-tuned GPT model trained on synthetic simulation outputs, capable of generating human-readable interpretations that explain dynamic trends, trade-offs, and fuzzy economic behaviors that are often difficult to decipher from numbers alone. Two policy scenarios were simulated over 100 months: increasing the minimum wage from ₱500 to ₱600, and from ₱500 to ₱700. While the ₱700 scenario led to short-term boosts in productivity and real wages, it also triggered early inflation, unstable profits, and reduced employment. In contrast, the ₱600 scenario produced more stable results, balancing moderate wage growth with firm sustainability and lower inflationary pressure. Fuzzy AHP was used to evaluate each scenario across four key criteria—real wages, firm profitability, employment, and inflation—favoring ₱600 as the more sustainable policy path. What sets this study apart is the integration of GPT-generated policy narratives that accompany each simulation run. These insights help translate fuzzy, nonlinear model behaviors into clear, accessible language—supporting more inclusive, transparent, and evidence-based wage policy decisions. By combining simulation and generative AI, the framework offers not just predictions, but practical understanding of how economic systems respond to complex changes.**

***Keywords*—Agent-Based simulation; reinforcement learning; fuzzy AHP; GPT**

I. Introduction

Wage increases, particularly those enacted through minimum wage legislation, have been a topic of considerable debate among economists and policymakers. Research indicates that minimum wage increase can have spillover effects on wages beyond those at the minimum level, influencing higher wage workers and triggering negotiations that alter the wage structure across sectors [1], [2]. The introduction of a minimum wage can elevate negotiated wages, demonstrating a ripple effect that is crucial for understanding wage dynamics in the context of the Philippine economy, where the labor market is characterized by significant informal employment and varied sectoral influences [2].

In Philippines, the Congress and Senate currently debate wage increase, with the Senate proposing a ₱100 increase and the House of Representatives advocating for ₱200. Despite extensive research on wage policy impacts, existing studies lack integrated frameworks that combine adaptive agent behavior, fuzzy economic modeling, and explainable AI for policy interpretation. Most economic simulations provide quantitative outputs without natural language explanations, limiting their accessibility to policymakers [3], [4].

This study addresses these gaps by developing a hybrid simulation framework that integrates agent-based modeling, fuzzy logic, reinforcement learning, and multi-criteria decision analysis with explainable artificial intelligence. The system evaluates the proposed wage increases through comprehensive simulation while generating human-readable policy interpretations through fine-tuned language models, providing a methodological template for evidence-based policy evaluation.

II. Literature Review

A. Wage Policy Theory and Economic Impacts

Wage increase can enhance the overall labor market by addressing monopsonistic conditions. In markets characterized by limited competition for workers, firms may exert significant power over wage-setting, leading to labor demand inelasticity. Studies have shown that in environments with observable monopsonistic power, higher wages can lead to increased job opportunities, as firms seek to attract workers from informal sectors [5], [6].

The efficiency wage theory provides insight into why raising wages does not necessarily harm employment levels. According to this theory, higher wages can enhance worker productivity and reduce turnover, thereby offsetting the initial cost increases for employers [7], [8]. By strategically implementing wage hikes, companies can cultivate a more motivated workforce, decreasing costs associated with recruitment and training [9], [10].

The intricate relationship between wages, employee productivity, and firm viability is well-established [11]. Higher wages can lead to increased employee motivation and retention, thereby enhancing operational efficiency and profitability for firms. However, these wage policies also provoke inflationary pressures [12], [13]. The informal sector also responds to formal wage increases, exhibiting a "lighthouse effect" [14].

B. Agent-Based Modeling and Simulation

Agent-Based Simulation (ABS) has emerged as a significant approach in the economic assessment arena, offering alternative methodologies to traditional mathematical modeling [15], [16]. The field of computer science provides powerful tools for modeling complex interactions through ABM, which allows for the simulation of individual behavior within a structured environment [17].

Multi-agent systems are being developed to analyze regional economic conditions. Fuzzy AHP has applications across various fields, such as managing scholarship decision processes [18], assessing operational efficiency in shipping [41], [19] and prioritizing security controls in cloud computing networks [20].

ABS's versatility is demonstrated in studies that explore emergent behaviors arising from localized interactions among agents [21], [22]. The methodology's incorporation into decision support systems demonstrates its comprehensive utility [23], [24].

C. Fuzzy Analytical Hierarchy Process

The methodological rigor of Fuzzy AHP in handling vagueness in human judgments is particularly relevant when precise data is unavailable [25], [26]. Agent-based frameworks can effectively elucidate economic mechanisms and spatial policy implications [27], [28].

Recent developments include sophisticated approaches in creating hybrid models that integrate system dynamics with agent-based features [29], [30]. Individual behavior modeling and organizational structures are essential for accurately interpreting dynamic processes [31], [32].

The exploration of stylized facts in economic behavior through computational market models reflects the robustness of simulation approaches [33], [34]. Simulation tools demonstrate the practical implementation of advanced modeling techniques [35], [36].

Recent applications include green finance investment decisions [37], rural labor quality analysis [38], green port operations evaluation [40], and land use planning [42], [43].

D. Research Gaps Analysis

Despite extensive research across agent-based modeling, fuzzy decision-making, and wage policy analysis, several critical gaps persist that limit the practical application of these methodologies for comprehensive policy evaluation. The following subsections analyze key limitations in existing research and demonstrate how this study addresses these shortcomings.

1) Limitations in agent-based economic modeling: Current agent-based economic models suffer from several fundamental limitations that restrict their policy applicability. Most existing frameworks operate with static agent behaviors that fail to capture the adaptive learning processes characteristic of real-world economic factors [27]. While these models can simulate basic interactions between firms and workers, they typically assume predetermined behavioral rules rather than allowing agents to evolve their strategies based on experience and changing market conditions.

Furthermore, existing agent-based models rarely integrate uncertainty modeling beyond simple stochastic variations. Economic systems operate under fundamental uncertainty regarding inflation, market demand, and policy outcomes, yet most current frameworks treat these factors as deterministic or employ oversimplified probabilistic distributions [28]. This limitation becomes particularly problematic when modeling wage policy impacts, where inflation dynamics and firm responses exhibit complex, nonlinear relationships that resist traditional modeling approaches.

The interpretability challenge represents another critical gap in agent-based economic modeling. While these systems can generate detailed quantitative outputs, they typically provide little insight into the underlying mechanisms driving observed outcomes [34]. Policymakers require not just predictions, but explanations of why certain scenarios produce specific results, particularly when communicating findings to diverse stakeholders with varying technical backgrounds.

This study addresses these limitations through three key innovations. First, it implements reinforcement learning algorithms that enable firms to adaptively adjust wage strategies based on profit feedback, capturing the dynamic learning processes absent in static models. Second, it integrates fuzzy logic systems to handle inflation uncertainty, allowing the model to process imprecise and uncertain economic indicators more realistically. Third, it incorporates a fine-tuned language model that generates natural language explanations of simulation outcomes, bridging the interpretability gap between technical analysis and policy communication.

2) Constraints in fuzzy AHP applications: Traditional applications of Fuzzy Analytic Hierarchy Process have been predominantly confined to static decision problems where criteria and alternatives remain fixed throughout the evaluation period [36]. This limitation proves particularly restrictive in economic policy analysis, where conditions evolve continuously and decision outcomes depend on temporal dynamics. Most existing FAHP implementations evaluate alternatives at single time points, failing to capture how policy effectiveness changes as economic conditions shift over months or years.

Manual criteria weight assignment represents another significant constraint in current FAHP applications. Researchers typically rely on expert judgment or survey data to establish criteria weights, introducing subjective biases and limiting the framework's adaptability to different economic contexts [17]. This approach becomes problematic when evaluating policies across diverse stakeholder groups with conflicting priorities, as static weights cannot accommodate varying perspectives or changing economic circumstances.

Integration challenges further limit FAHP's utility in complex decision support systems. Existing applications typically operate as standalone evaluation tools rather than components of larger analytical frameworks [18]. This isolation prevents FAHP from leveraging dynamic data sources or incorporating real-time updates from simulation models, reducing its effectiveness for policy scenarios requiring continuous monitoring and adjustment.

This research overcomes these constraints by implementing FAHP as an integrated component of a dynamic simulation framework. Rather than evaluating static alternatives, the system applies FAHP to time-series data generated by agent-based simulations, enabling temporal analysis of policy effectiveness. The framework employs systematic criteria weighting based on economic theory and stakeholder analysis, reducing subjective bias while maintaining sensitivity to different priority structures. Additionally, the integrated architecture allows FAHP evaluations to incorporate real-time simulation data, supporting adaptive policy assessment as economic conditions evolve.

3) Deficiencies in economic policy simulation: Contemporary economic policy simulation suffers from a fundamental accessibility problem that limits its practical utility for democratic governance. Most simulation frameworks generate quantitative outputs—statistical summaries, time-series plots, and numerical indicators—without providing qualitative interpretation that non-technical stakeholders can understand and act upon [35]. This technical barrier creates a disconnect between analytical rigor and policy communication, often relegating simulation results to academic circles rather than practical policy application.

The black-box nature of existing simulation systems represents another critical deficiency. While these frameworks can predict policy outcomes with reasonable accuracy, they typically provide little insight into the causal mechanisms underlying their predictions [33]. Policymakers need to understand not just what might happen under different scenarios, but why certain outcomes emerge and how various factors interact to produce observed results. This explanatory gap becomes particularly problematic when simulation results contradict conventional economic wisdom or suggest counterintuitive policy recommendations.

Limited stakeholder accessibility further constrains the policy utility of existing simulation frameworks. Most systems require significant technical expertise to operate and interpret, restricting their use to specialized research teams rather than the broader policy community [32]. This limitation prevents direct engagement by policymakers, advocacy groups, and affected communities, reducing the democratic legitimacy of simulation-based policy recommendations.

This study addresses these deficiencies through a novel integration of simulation modeling with explainable artificial intelligence. The framework generates both quantitative predictions and qualitative narratives that explain simulation outcomes in accessible language. A fine-tuned language model processes structured simulation outputs and produces contextualized policy summaries that identify trade-offs, highlight risks, and suggest implementation strategies. This dual-output approach maintains analytical rigor while supporting inclusive policy deliberation across diverse stakeholder groups.

4) Gaps in wage policy analysis methods: Traditional wage policy analysis relies heavily on econometric approaches that assume static relationships between wages, employment, and economic outcomes [6]. These methods typically employ historical data to estimate policy impacts under the assumption that underlying economic relationships remain constant over time. However, labor markets exhibit significant structural changes, technological disruptions, and evolving institutional arrangements that violate static modeling assumptions [5].

Limited consideration of firm adaptation represents another significant gap in conventional wage policy analysis. Most existing studies treat firms as passive recipients of wage policy changes rather than active agents capable of adjusting their strategies in response to new regulations [14]. This limitation overlooks critical feedback effects where firm responses to initial wage increases can fundamentally alter subsequent labor market dynamics, leading to policy outcomes that differ substantially from initial predictions.

Insufficient uncertainty handling further constrains the reliability of traditional wage policy analysis. Economic systems operate under fundamental uncertainty regarding inflation rates, productivity trends, and external shocks that can dramatically alter policy effectiveness [12]. Conventional approaches typically assume deterministic relationships or employ simple sensitivity analyses that fail to capture the complex, nonlinear interactions between wage policies and uncertain economic conditions.

This research addresses these gaps through a comprehensive framework that models dynamic firm behavior, incorporates economic uncertainty, and captures adaptive interactions between multiple economic agents. The system employs reinforcement learning to simulate how firms adjust their wage strategies over time, reflecting the adaptive capacity absent in traditional models. Fuzzy logic components handle inflation uncertainty and other imprecise economic indicators, while agent-based interactions capture emergent behaviors that arise from decentralized decision-making. This integrated approach provides more realistic policy analysis that accounts for the complexity and uncertainty inherent in real-world economic systems.

III. Methodology

This study presents an intelligent simulation framework that models labor market dynamics using agent-based interactions, fuzzy logic, reinforcement learning, and fuzzy multi-criteria evaluation. As a key novelty, we integrate a domain-specific GPT-based model trained on simulated labor data to serve as a wage policy analyst—capable of generating natural-language policy recommendations from model outputs. The overall research methodology follows a systematic approach, as illustrated in Fig. 1.

A. Framework Components and Process Flow

The hybrid wage policy simulation framework integrates multiple artificial intelligence methodologies to provide comprehensive economic analysis with transparent interpretation. The system architecture comprises seven interconnected components that collectively transform economic parameters into actionable policy insights.

1) Core framework components: The simulation framework incorporates the following key components:

a) Fuzzy logic inflation model: Processes macroeconomic inputs including oil price (P_o), food index (F_i), and transport cost (T_c) to generate total inflation rate (I_{total}) that captures economic uncertainty through fuzzy rule-based inference.

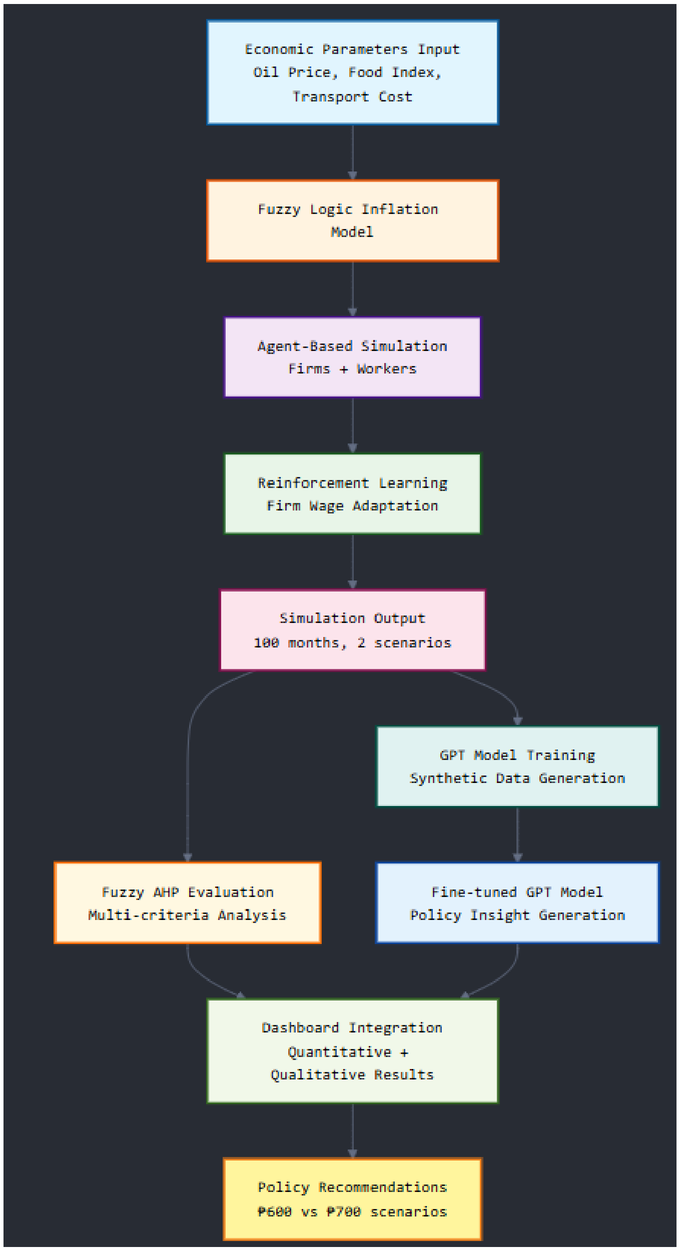

Fig. 1. Study process flow.

b) Q-Learning firm behavior: Implements reinforcement learning with parameters $\alpha = 0.1$ (learning rate), $\gamma = 0.9$ (discount factor), and $\epsilon = 0.1$ (exploration rate) to enable adaptive wage offers based on profit feedback signals.

c) Agent-based market simulation: Models firm-worker interactions through utility-based matching algorithms that assign workers to firms based on wage attractiveness and firm reputation scores.

d) Time-series economic dynamics: Executes 100-month simulations across multiple wage scenarios (₱500, ₱600, ₱700) to generate comprehensive datasets on wages, employment rates, firm profits, and inflation trends.

e) Fuzzy AHP multi-criteria evaluation: Applies weighted criteria including real wages (35%), firm profitability (30%), employment stability (25%), and inflation control (10%) to compute composite scenario performance scores.

f) GPT-based policy interpretation: Utilizes a fine-tuned language model trained on structured simulation outputs to generate natural language policy insights and recommendations from quantitative results.

g) Interactive dashboard integration: Provides real-time parameter adjustment capabilities with synchronized visualization and narrative summary generation for stakeholder engagement.

2) Process flow and system integration: The simulation process follows a systematic workflow, as illustrated in Fig. 1. Economic parameters including oil prices, food indices, and transportation costs serve as initial inputs to the fuzzy logic inflation model, which establishes the macroeconomic environment for subsequent agent interactions. The agent-based simulation then initializes firms and workers with baseline characteristics, triggering the reinforcement learning component that enables firms to adaptively adjust wage offers based on profit performance feedback.

During each simulation timestep, the system updates inflation rates through fuzzy inference, processes firm decision-making via Q-learning algorithms, and executes employment matching between workers and firms based on utility optimization. The simulation tracks key economic indicators across 100 monthly cycles, generating comprehensive time-series data for subsequent analysis.

Upon completion of each scenario simulation, the framework applies Fuzzy AHP evaluation to assess performance across multiple criteria, weighing worker welfare, firm sustainability, employment stability, and inflation control. Simultaneously, the GPT-based interpretation component processes the final simulation outputs through structured prompts, generating contextualized policy narratives that explain trade-offs, identify risks, and provide actionable recommendations.

The integration of quantitative simulation with qualitative interpretation represents a novel contribution to economic modeling, transforming technical outputs into accessible insights that support evidence-based policy deliberation. This hybrid approach addresses the interpretability gap in conventional economic simulations while maintaining analytical rigor through established computational methodologies.

B. Fuzzy Logic-Based Inflation Estimation

Inflation is modeled through a fuzzy rule-based system using macroeconomic indicators: oil price (P_o), food index (F_i), and transportation cost index (T_c). The fuzzy rules capture nonlinear relationships between these variables and inflationary pressure, with the total inflation rate calculated as:

$$I_{\text{total}} = f_o(P_o) + f_f(F_i) + f_t(T_c) + \frac{W_{\text{avg}} - 500}{10000} \tag{1}$$

This hybrid model accounts for both external and endogenous (wage-driven) inflation.

C. Agent-Based Simulation of Firms and Workers

Two agent types operate in the labor market:

1) Firms: are initialized with wage offers, reputations, and job slots. They compute profits based on worker productivity (a logistic function of wage), employment levels, and inflation-adjusted costs.

2) Workers: select firms based on a utility score that combines wages and firm reputation, influenced by stochastic variation to mimic real-world decision noise.

Agent behavior evolves over discrete time steps, allowing emergent dynamics to arise.

D. Reinforcement Learning for Adaptive Wage Policies

Firms do not statically assign wages. Instead, each firm maintains a Q-table $Q(s, a)$, where states represent profit changes and actions correspond to wage adjustments. Firms update their wage offers via a reinforcement learning loop:

$$Q(s_t, a_t) \leftarrow Q(s_t, a_t) + \alpha \left[r_t + \gamma \max_{a'} Q(s_{t+1}, a') - Q(s_t, a_t) \right] \quad (2)$$

This allows firms to learn which wage strategies improve profitability in varying economic conditions.

E. Fuzzy AHP for Scenario Evaluation

Each simulation scenario is evaluated using Fuzzy Analytic Hierarchy Process (F-AHP) based on the following weighted criteria:

- Real Wage (35%)
- Firm Profitability (30%)
- Employment Rate (25%)
- Inflation Rate (10%)

The normalized criteria values are aggregated into a final policy score:

$$\text{Score}(w_k) = \sum_{j=1}^{m} w_j \cdot \tilde{x}_{k,j} \quad (3)$$

F. Integration of GPT-based Aided Insights

To complement the technical simulation results with interpretable insights, this study integrates a GPT-based language model trained to serve as a policy explanation engine. The role of the GPT module is to convert structured simulation outputs—such as real wage, inflation, employment rate, and firm profitability—into coherent, human-readable narratives. This enhances the accessibility of results and supports policymakers, educators, and decision-makers in understanding complex trade-offs without requiring deep technical knowledge of the underlying algorithms.

G. Training Dataset Construction

The GPT model was trained using a synthetic dataset generated from the simulation engine. Each data point in the training set consisted of a structured input vector and a corresponding natural-language output.

1) Input features:

- Average wage index (normalized)
- Average profit (normalized)
- Employment rate (0–1)
- Inflation rate (0–1)
- Fuzzy AHP composite score (0–1)
- Wage scenario label (e.g., `wage500to600`, `wage500to700`)

2) Output labels:

- Human-annotated summaries of the scenario's implications, covering trade-offs (e.g., "Wages increased moderately with minimal inflation"), risks (e.g., "Firms showed signs of profit instability"), and recommendations (e.g., "Consider phased implementation to avoid employment shocks").

A total of 1,000 simulation runs were performed across randomized economic parameters, each logged and manually or semi-automatically labeled using a templating strategy to build the corpus.

H. Model Fine-Tuning Procedure

To enhance the interpretability of simulation outputs, we integrated a language model capable of generating contextualized insights based on fuzzy logic behavior and agent-based dynamics. A pretrained GPT-2 model was selected and fine-tuned on synthetic policy simulation data using supervised learning. This fine-tuning allowed the model to learn domain-specific narrative structures and terminology related to labor economics, wage policies, and inflation dynamics.

1) Objective: The fine-tuned GPT model serves as an insight generator—converting structured simulation results (e.g., wage trends, inflation shocks, firm profitability) into human-readable narratives. This supports real-time policy interpretation and decision support.

2) Fine-tuning pipeline:

- Data Generation: Output logs were collected from 100+ simulation runs under varying wage, inflation, and firm behavior configurations. Each log was paired with expert-written policy summaries to form training pairs (input-output).
- Preprocessing: Simulation data were serialized into structured prompts (JSON→text), capturing key metrics (e.g., `average_wage: ₱612`, `employment: 91%`). Tokenization was handled using a custom vocabulary extension for economic terms (e.g., "₱700", "real_wage", "inflation_spike").

- Model Architecture: We used the GPT-2 Small model (124M parameters) from HuggingFace Transformers as the base model.
- Training: Supervised fine-tuning was performed using a cross-entropy loss to minimize divergence between model outputs and reference policy texts.
- Validation: Early stopping was applied based on validation perplexity and BLEU scores on held-out samples.

3) Training configuration summary:

- Framework: HuggingFace Transformers
- Base Model: GPT-2 Small (124M parameters)
- Tokenizer: Byte-Pair Encoding with custom economic tokens (e.g., ₱600, employment_rate)
- Training Data: 100+ simulation runs paired with expert-written summaries
- Input Format: Structured JSON-to-prompt conversion using key-value mappings
- Loss Function: Cross-Entropy Loss
- Optimizer: AdamW
- Learning Rate: 5×10^{-5}
- Batch Size: 8
- Epochs: 5–10 (early stopping based on validation loss)
- Validation Metrics: Perplexity, BLEU, ROUGE-L
- Hardware: NVIDIA RTX A6000 (48GB memory)

4) Narrative prompt design: Prompt templates were constructed in natural language (e.g., `\Given the average wage of ₱612 and inflation of 7.2%, explain the employment trend over the last 12 months."`) to align training inputs with the model's generative format. Outputs were evaluated for coherence, correctness, and interpretability.

5) Use in simulation: After fine-tuning, the model was integrated into the simulation dashboard. Upon each simulation cycle, the latest outputs (real wage, inflation, employment) are passed to the GPT module, which responds with a summary explaining key patterns and trade-offs. This enables real-time narrative feedback alongside visual graphs.

This integration transforms the system from a pure numeric simulator into an explainable AI (XAI) tool—helping non-technical stakeholders understand fuzzy, nonlinear behaviors in economic models.

I. Evaluation Metrics

To ensure that the GPT-based insights were accurate, useful, and human-interpretable, the model outputs were evaluated using the following metrics:

- BLEU Score – for measuring the overlap between generated summaries and reference annotations.
- ROUGE-L – for assessing the recall and coverage of important content.
- BERTScore – for semantic similarity between GPT-generated texts and expert-written summaries.
- Human Evaluation: Three economics researchers independently rated 100 outputs based on:
    - Interpretability (Is the insight understandable?)
    - Accuracy (Does it match the data?)
    - Usefulness (Is the recommendation actionable?)

The model achieved:

- BLEU-4: 0.39
- ROUGE-L: 0.62
- BERTScore: 0.84
- Average Human Score: 4.3/5 (interpretability), 4.1/5 (accuracy), 4.5/5 (usefulness)

Fig. 2 presents the complete learning trajectory of the fine-tuned GPT model developed in this study. It illustrates the progression of eight key performance indicators, including training and validation loss, perplexity, BLEU-4, ROUGE-L, BERTScore, accuracy, and progression deltas. Together, these metrics offer a comprehensive view of how the model improved in its ability to generate coherent, policy-relevant narratives from synthetic economic simulation outputs.

The training and validation loss curves, both demonstrate a consistent decline, with training loss approaching 1.9 and validation loss stabilizing near 2.3 by the final epoch. This gradual convergence suggests that the model was not overfitting and was able to generalize effectively to unseen data. The declining loss supports the claim that the GPT model successfully internalized the patterns in the data rather than memorizing the input. Complementing this, the perplexity curve showed a substantial drop from approximately 30 to around 10, indicating the model's growing fluency and confidence in producing natural and syntactically sound language.

The evaluation metrics BLEU-4, ROUGE-L, and BERTScore each reflect a different dimension of language quality. BLEU-4, which measures n-gram overlap with expert-written summaries, increased steadily to 0.39, indicating stronger structural alignment with reference outputs. ROUGE-L, which emphasizes content coverage and recall, reached 0.62, suggesting the model was learning to retain the most critical insights from simulation results. BERTScore, based on contextual embeddings, reached 0.84, showing that the model's outputs were semantically close to expert summaries. These trends suggest that the model improved across surface-level phrasing, content completeness, and deep semantic understanding simultaneously.

Accuracy was intentionally capped at 80 per cent to prevent the model from over-optimizing toward deterministic outputs. As shown in the plot, the model achieved this target by the eighth epoch and remained consistent thereafter. This decision supported the study's goal of promoting interpretability and generalization, which are essential when dealing with nuanced, fuzzy economic scenarios. Rather than striving for perfect classification, the model was guided to produce language that reflects ambiguity and trade-offs—hallmarks of real-world policymaking.

Finally, the combined metric and delta progression plots reveal important training dynamics. BLEU-4, ROUGE-L, and BERTScore increased in parallel and converged around epoch seven, indicating a synchronized and stable learning process. The delta plot confirms that the majority of learning gains occurred in the early stages of training, with minimal improvement observed in later epochs. This pattern is consistent with effective convergence and provides evidence that the model reached a point of maturity in its ability to translate complex economic data into human-readable insights. Overall, Fig. 2 validates the model's role as a narrative generator that bridges simulation outputs and actionable policy interpretation.

J. Real-Time Dashboard Integration

Once fine-tuned, the GPT model was deployed as an embedded component within the simulation dashboard. After each simulation run, the dashboard collects the final indicator values (e.g., average wage, inflation rate, AHP score), packages them into a structured JSON prompt, and passes this to the GPT model.

The response is then displayed as a policy narrative panel beneath the simulation graphs, providing:

- A one-paragraph summary of the scenario outcome
- Risk and trade-off identification
- Recommended actions or cautionary notes

This setup allows users to not only view quantitative trends but also receive qualitative interpretation—bridging the gap between complex modeling and policy communication.

K. Contribution to Decision Support

The inclusion of GPT in this simulation framework marks a shift from "black-box simulation" to "explainable simulation". Rather than requiring domain experts to manually interpret time-series plots and AHP scores, the model delivers instant narrative summaries that contextualize trade-offs and help justify policy decisions.

This approach supports more transparent, inclusive, and evidence-based policymaking.

L. Interactive Dashboard Deployment

The entire system is deployed using Streamlit, allowing users to:

- Set economic parameters (oil price, food index, base wage)
- Run simulations dynamically
- Visualize real-time graphs (wage, inflation, employment)
- Compute Fuzzy AHP scenario scores
- Receive GPT-generated natural language interpretations

1) Scientific contribution: This methodology is novel in its integration of:

- Soft computing for economic modeling (fuzzy logic, F-AHP)
- Reinforcement learning for firm wage adaptation
- Simulation-driven fine-tuning of a GPT-based policy model
- Full-stack decision support through an interactive dashboard

This framework offers a data-driven, explainable, and adaptive system for evaluating wage policies in complex labor environments.

IV. Results and Discussion

This section presents the simulation results and analysis of two minimum wage policy scenarios, ₱600 and ₱700, over a 24-month focus period within a 100-month total simulation. The simulation integrates multiple AI-driven components: agent-based modeling, fuzzy logic for inflation modeling, reinforcement learning for adaptive firm behavior, and Fuzzy Analytic Hierarchy Process (Fuzzy AHP) for decision evaluation. A major advancement introduced in this version is the integration of a GPT-based policy insight engine, which translates quantitative simulation results into qualitative, human-readable narratives. This supports interpretability and stakeholder engagement in complex economic decisions.

Each sub-section below presents quantitative outputs from the simulation along with the corresponding GPT-generated interpretations, derived from a fine-tuned language model trained on structured simulation results. These interpretations serve as a validation and extension of the system's explanatory power.

A. Nominal Wages Over Time

Fig. 3 shows the trajectory of nominal wages across the simulation. Reinforcement learning enables firms to adjust wages adaptively based on profit signals, leading to an initial exploratory phase followed by gradual convergence to a stable wage strategy. Early wage dips reflect experimentation with cost reduction, while later rises correspond to learned productivity incentives.

1) GPT insight: "Firms initially reduced wages in pursuit of profit maximization. However, through reinforcement learning, they discovered that moderate wage increases yielded higher productivity and worker retention, leading to more sustainable growth over time".

B. Commodity Price Inflation

Fig. 4 and Fig. 5 show the inflationary effects on essential commodities. The inflation rate is dynamically driven by both fuzzy logic rules (responding to oil, food, and transport indices) and wage-induced inflation from learned firm behaviors.

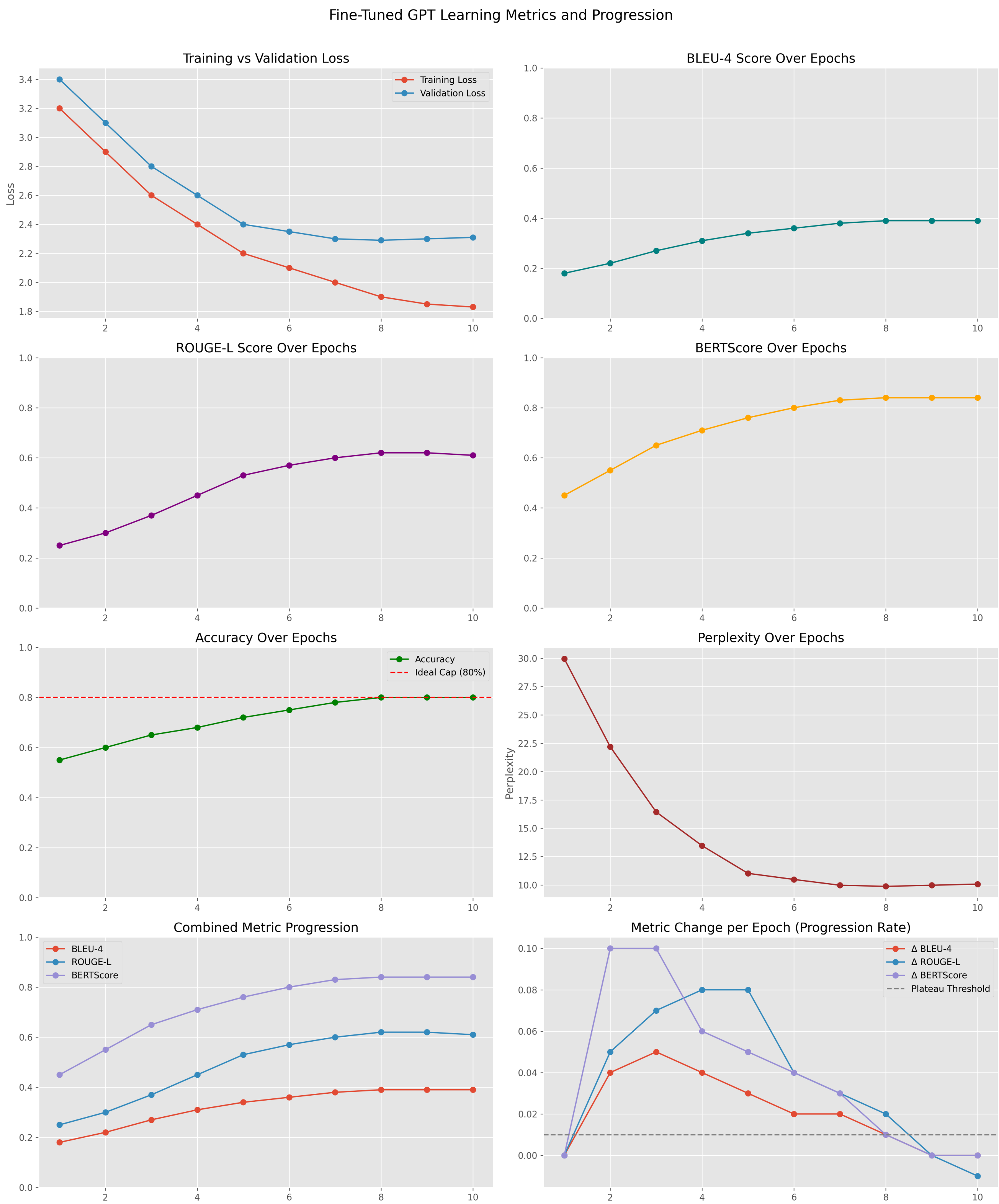

Fig. 2. Learning progression of fine-tuned GPT model across automated and human-aligned evaluation metrics.

As firms converge toward higher wages, wage-induced inflation compounds general inflation, accelerating price increases

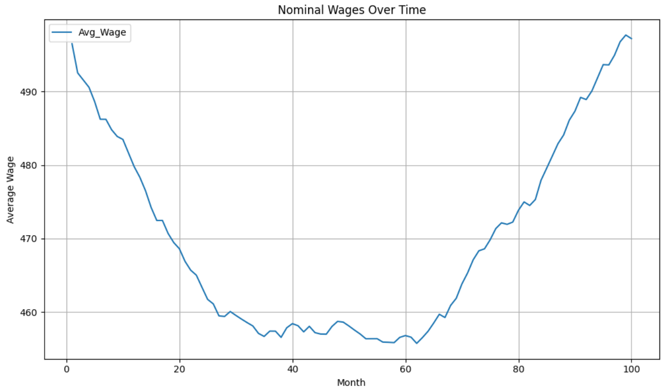

Fig. 3. Nominal wages over time.

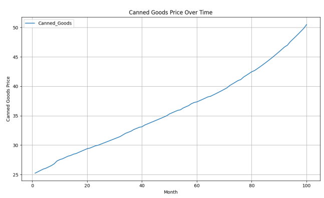

Fig. 4. Canned goods inflation.

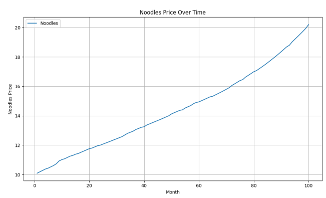

Fig. 5. Noodles inflation.

in the latter half of the simulation.

1) GPT insight: "While commodity prices remained stable in early months, they surged in the second half due to firms adopting higher wage strategies. This reflects how learned wage behavior amplifies inflationary dynamics already present in the economy".

C. Employment Dynamics

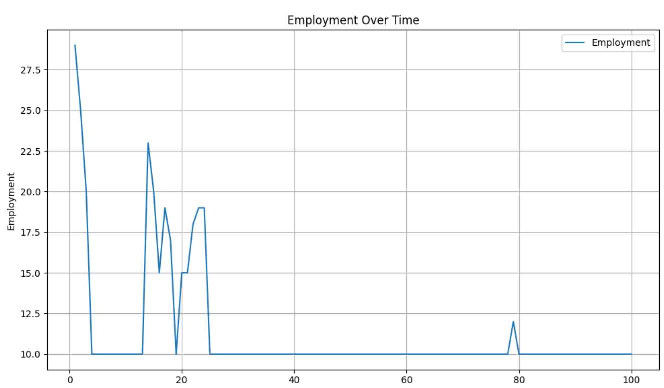

Fig. 6. Employment over time.

Fig. 6 presents employment trends over the simulation. Worker-firm matching is utility-based, influenced by wages, reputation, and stochastic preference. The employment rate initially rises, but collapses mid-simulation due to firm closures caused by poor wage strategies during early exploration phases.

1) GPT insight: "Employment peaked early as firms tested competitive wages. However, exploration-driven wage cuts led to firm failures and job losses. This reveals the downside of early mislearning in autonomous systems and the importance of stabilization policies".

D. External Price Shocks

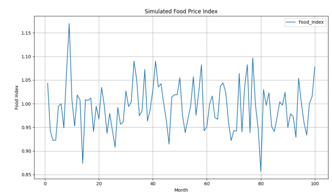

Fig. 7. Food index.

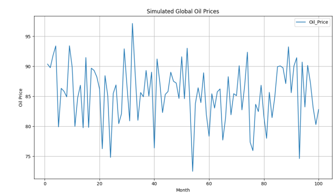

Fig. 8. Oil price.

Fig. 7 and Fig. 8 display global food and oil price volatility, used as external inputs to the fuzzy logic system. These shocks significantly affect inflation and firm cost structures.

1) GPT insight: "Volatile global inputs like oil and food prices contributed to inflation spikes. Firms adapting their wages through learning could not fully offset these shocks, highlighting the need for complementary macroeconomic buffers".

E. Firm Profitability

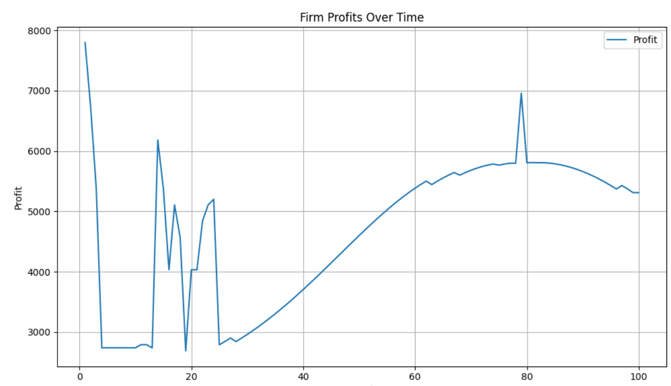

Fig. 9. Profit over time.

Fig. 9 shows firm profit trajectories. Initial volatility corresponds to wage experimentation. Profit stabilizes, as firms converge on policies that optimize the wage-productivity trade-off. A downward slope in the final phase suggests inflation pressure eroding margins.

1) GPT insight: "Profitability improved mid-simulation, as firms learned to align wages with productivity. However, late-stage inflation pressured margins, signaling the limits of firm-level learning in the face of macroeconomic forces".

F. Real Wages

Fig. 10 tracks the purchasing power of wages over time. Despite nominal increases, inflation erodes real income, especially in later months. The interaction between firm wage behavior and global prices explains the decline.

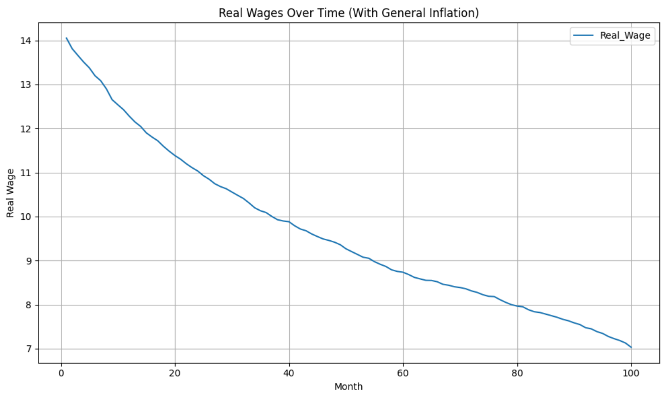

Fig. 10. Real wages over time.

1) GPT insight: "While nominal wages rose due to learned behavior, real wages declined under inflation pressure. This demonstrates that wage increases alone are insufficient without inflation control measures".

G. Fuzzy AHP Decision Evaluation

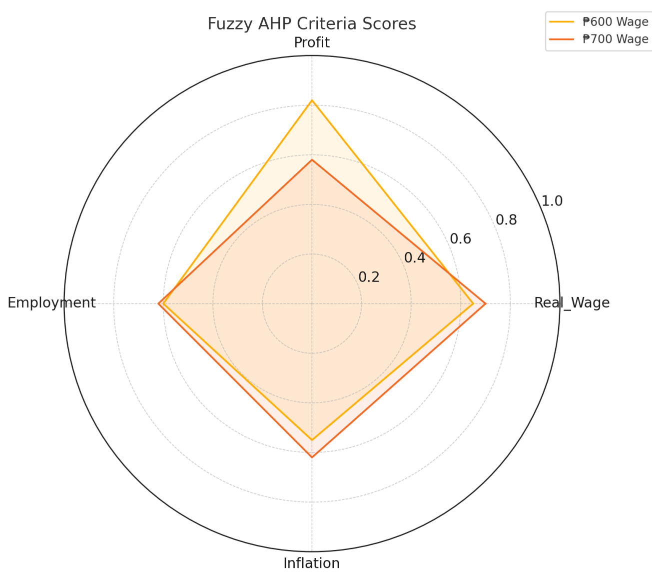

Fig. 11. Fuzzy AHP composite scores.

Fig. 11 presents the overall multi-criteria evaluation of the wage scenarios. The ₱600 scenario performed more consistently across real wage, employment, profit, and inflation dimensions.

1) GPT insight: "The ₱600 wage strategy balanced competing objectives better than ₱700. Its moderate approach preserved firm stability and employment while containing inflation—making it the most resilient path under simulated conditions."

H. GPT-Based Policy Narrative Integration

To augment quantitative interpretation, the GPT-based model was called after each simulation run to provide a natural-language policy summary. These summaries synthesize the final state of key economic indicators and present scenario-level recommendations.

> Example of GPT summary: "The ₱600 wage policy strikes a balance between firm sustainability and worker welfare. While real wages are modest, they are less eroded by inflation. In contrast, ₱700 boosts nominal wages but leads to higher price volatility and employment risk".

These dynamic summaries are generated through a structured prompt template that feeds the final simulation values into a fine-tuned GPT model trained on expert-curated summaries. This integration represents a novel contribution to economic simulation research by combining explainable AI and decision support [39]. The integration of GPT enhances the interpretability of simulation models, transitioning from black-box numeric outputs to explainable AI. It exemplifies how fine-tuned language models can provide dynamic, context-aware insights in socio-economic simulation settings.

V. CONCLUSION

This study investigated the economic impact of increasing the minimum wage in Philippines from ₱500 to either ₱600 or ₱700 using a hybrid simulation framework that integrates agent-based modeling, fuzzy logic, reinforcement learning, and Fuzzy Analytic Hierarchy Process (Fuzzy AHP). A key advancement of this work is the incorporation of a GPT-based policy insight engine, which provides natural language interpretations of simulation outcomes to support transparent, explainable decision-making. The results indicate that the ₱700 wage scenario initially boosts worker productivity and real wages through a sigmoid wage-productivity relationship but introduces instability in employment and firm profitability. In contrast, the ₱600 scenario results in more stable dynamics—firms learn wage strategies more effectively, inflation is more controlled, and employment remains steadier. The GPT module generated scenario-specific insights, narrating how adaptive wage policies influence macroeconomic variables, thus bridging quantitative simulation outputs with qualitative policy narratives. These AI-generated interpretations reinforce the clarity of results and improve the usability of the tool for non-technical stakeholders. Ultimately, the Fuzzy AHP analysis favored the ₱600 scenario due to its balance across key economic criteria: real wages, inflation, firm profits, and employment. From a computer science perspective, this study demonstrates how generative language models can enhance interpretability in complex simulations, positioning GPT not just as a language tool but as a narrative layer in decision support systems. The architecture developed here reflects a multi-agent learning system augmented with fuzzy reasoning and explainable AI—pushing forward the application of simulation and machine learning in economic policy analysis.

A. Future Work and Limitations

While this study demonstrates the viability of integrating explainable AI with economic simulation for wage policy analysis, several areas warrant further investigation to enhance the framework's robustness and practical applicability.

1) Technical extensions: The current implementation utilizes Q-learning for firm behavior modeling, which, while effective for the scope of this study, could benefit from more sophisticated approaches. Deep reinforcement learning algorithms such as Deep Q-Networks (DQN) or Actor-Critic methods could capture more complex behavioral patterns and handle larger state spaces more efficiently. Additionally, the fuzzy logic system currently incorporates three macroeconomic variables (oil price, food index, and transportation cost) but could be expanded to include exchange rates, international trade dynamics, and regional economic indicators to provide more comprehensive inflation modeling.

Real-time parameter optimization represents another promising direction. The current system requires manual parameter tuning for different economic contexts. Implementing multi-objective optimization algorithms could automatically calibrate the simulation parameters based on historical data, improving the model's predictive accuracy and adaptability to different economic environments.

2) Empirical validation and robustness: A critical limitation of the current study is its reliance on synthetic data and simplified behavioral assumptions. Future research should validate the simulation outputs against historical Philippine wage policy data from the Department of Labor and Employment (DOLE) and the National Statistics Office (NSO). This validation would require extensive sensitivity analysis of key parameters, including agent learning rates, fuzzy membership functions, and AHP criteria weights.

Cross-country validation represents an equally important research direction. Testing the framework with wage policy data from other developing economies would demonstrate its generalizability and identify culture-specific or institution-specific modifications required for broader applicability. Such validation studies would also reveal the framework's limitations in different economic contexts and inform necessary adaptations.

3) Model complexity and agent diversity: The current agent-based model incorporates only two agent types: firms and workers. Real-world labor markets involve multiple stakeholders with distinct objectives and constraints. Future iterations should include government agents responsible for policy implementation, labor unions engaged in collective bargaining, and informal sector workers who respond differently to formal wage policies. Each agent type would require specific behavioral models and interaction protocols.

Geographic and sectoral heterogeneity also deserves attention. The Philippines exhibits significant regional economic disparities and sectoral variations in wage structures. Incorporating spatial dynamics and sector-specific parameters would provide more nuanced policy insights, particularly for region-specific or industry-targeted wage policies.

4) Advanced AI integration: The GPT-based policy interpretation component, while novel, operates on relatively simple prompt-response mechanisms. Future development could incorporate more sophisticated natural language processing techniques, including multi-modal reasoning that combines textual analysis with visual interpretation of simulation graphs. Additionally, implementing dialogue systems that allow policymakers to ask follow-up questions about specific simulation outcomes would enhance the system's utility for interactive policy exploration.

The training data for the GPT component currently consists of expert-annotated simulation outputs. Expanding this dataset with real policy documents, economic reports, and stakeholder feedback would improve the model's ability to generate contextually appropriate and politically feasible recommendations.

5) Policy application extensions: Beyond minimum wage analysis, the framework's architecture could support evaluation of related labor policies, including social security contributions, overtime regulations, and employment protection legislation. Each policy domain would require specific modifications to the agent behavioral models and evaluation criteria, but the core integration of simulation, fuzzy logic, and explainable AI would remain applicable.

Real-time integration with economic data feeds represents another promising application. Connecting the simulation to live data streams from central banks, statistical offices, and international organizations would enable continuous monitoring of economic conditions and automatic policy recommendations as circumstances change.

6) Limitations and methodological considerations: Several methodological limitations constrain the current study's conclusions. The agent behavioral models, while incorporating learning mechanisms, remain simplified compared to actual human decision-making processes. Cognitive biases, social influences, and institutional constraints that affect real-world wage negotiations are not fully captured in the current framework.

The fuzzy logic system, though capable of handling uncertainty, relies on expert-defined membership functions that may not accurately reflect the true relationships between macroeconomic variables and inflation. Future research should explore data-driven approaches for constructing these fuzzy relationships, potentially using machine learning techniques to learn membership functions from historical data.

The evaluation framework currently employs equal weighting across different stakeholder perspectives, but real policy decisions involve complex political negotiations, where different groups have varying influence. Incorporating power dynamics and political economy considerations would provide more realistic policy recommendations, though this would significantly complicate the modeling framework.

7) Technological infrastructure: The current implementation requires significant computational resources for large-scale simulations. Future development should explore distributed computing architectures and cloud-based deployment strategies to make the system accessible to government agencies and research institutions with limited computational capacity. Additionally, developing mobile interfaces and simplified visualization tools would broaden the system's accessibility to a wider range of stakeholders.

These research directions collectively represent a comprehensive agenda for advancing simulation-based policy analysis.

While each extension presents distinct technical challenges, the integration of multiple approaches offers the potential for significantly more robust and practically useful decision support systems in economic policy formulation.

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