
AGENTIC WORKFLOWS FOR ECONOMIC RESEARCH: DESIGN AND IMPLEMENTATION

A PREPRINT

Herbert Dawid

Faculty of Business Administration and Economics
Universität Bielefeld
Germany, 33615
hdawid@uni-bielefeld.de

Philipp Harting

Research Group in Law, Economics, Management
Côte d'Azur University
Av. Valrose, 06000 Nice, France
Philipp-Clemens.HARTING@univ-cotedazur.fr

Hankui Wang

Faculty of Business Administration and Economics
Universität Bielefeld
Germany, 33615
hankui.wang@uni-bielefeld.de

Zhongli Wang

Faculty of Business Administration and Economics
Universität Bielefeld, Germany
Department of Economics & Finance
Università Cattolica del Sacro Cuore, Italy
zhongli.wang@uni-bielefeld.de

Jiachen Yi

Department of Economics, Cardiff Business School
Cardiff University
United Kingdom, CF10 3EU
yij3@cardiff.ac.uk

April 15, 2025

ABSTRACT

This paper introduces a methodology based on agentic workflows for economic research that leverages Large Language Models (LLMs) and multimodal AI to enhance research efficiency and reproducibility. Our approach features autonomous and iterative processes covering the entire research lifecycle—from ideation and literature review to economic modeling and data processing, empirical analysis and result interpretation—with strategic human oversight. The workflow architecture comprises specialized agents with clearly defined roles, structured inter-agent communication protocols, systematic error escalation pathways, and adaptive mechanisms that respond to changing research demand. Human-in-the-loop (HITL) checkpoints are strategically integrated to ensure methodological validity and ethical compliance. We demonstrate the practical implementation of our framework using Microsoft's open-source platform, AutoGen, presenting experimental examples that highlight both the current capabilities and future potential of agentic workflows in improving economic research.

Keywords Economic research · AI Agents · Agentic Workflows · LLMs · Multimodal

1 Introduction

The integration of AI (Artificial Intelligence) into academic research workflows represents a paradigm-shifting potential for economics. As computational capabilities expand and AI systems become more powerful, economists face the prospect of leveraging intelligent agents to strengthen traditional research methodologies. These "agentic workflows"—defined as AI-assisted research processes with varying degrees of autonomy—offer possibilities for accelerating discovery and enhancing reproducibility.

Economic research requires labor-intensive processes for literature review, data processing, and empirical validation, with researchers often struggling to manage the exponentially growing volume of literature and complex datasets. Agentic workflows offer solutions to these persistent challenges by automating routine tasks, supporting sophisticated analyses, and facilitating novel interactions with research materials. The potential benefits for economics are multifaceted: broadening participation in high-level analytical approaches, dramatically reducing time spent on data preprocessing, and enabling more literature reviews that would be infeasible through manual methods alone. Furthermore, by documenting research steps in executable formats, these workflows enhance transparency and reproducibility.

While a growing ecosystem of AI-powered research tools exists—spanning commercial platforms like Elicit, SciSpace, OpenAI’s Deep Research, and Google’s Gemini Deep Research to open-source initiatives like Stanford’s STORM and Google’s Co-Scientist—economics as a discipline has been relatively slow to adapt these technologies to its specific methodological needs. Our systematic analysis of 421 studies from Google Scholar most closely related to “agentic workflow” (2001-2025) reveals a striking disciplinary imbalance. When categorized according to the International Standard Classification of Education framework (UNESCO, 2015), only 19 studies (4.5%) fall within “Social Sciences, Journalism, and Information” (Category 03). Even more revealing, economic research accounts for merely 4 of these 19 studies—highlighting an opportunity for pioneering work in this domain.

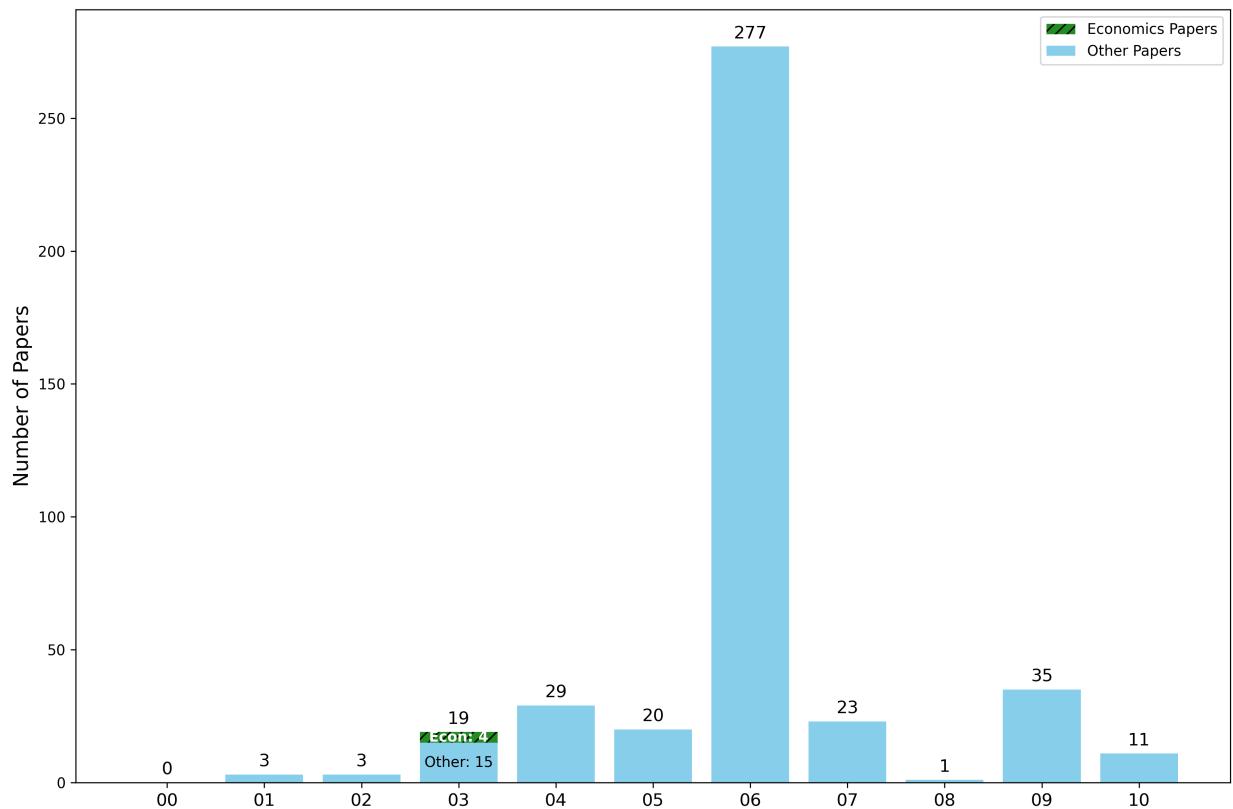


Figure 1: Applications of Agentic Workflows in Scientific Research by Discipline.

Note: ISCED categories 00: Generic programmes and qualifications; 01: Education; 02: Arts and humanities; 03: Social sciences, journalism and information; 04: Business, administration and law; 05: Natural sciences, mathematics and statistics; 06: Information and communication technologies; 07: Engineering, manufacturing and construction; 08: Agriculture, forestry, fisheries and veterinary; 09: Health and welfare; 10: Services.

Despite this limited presence, our temporal analysis reveals a striking trend: research on agentic workflows has experienced rapid acceleration in recent years (Figure 2). This surge coincides with significant advancements in LLM capabilities, suggesting we are at an inflection point where these technologies are becoming mature enough for serious scientific application. This expanding ecosystem of tools and growing publication volume signals both the increasing recognition of agentic workflows’ value and creates an urgent imperative for economists to engage substantively with these methodologies—shaping their development before practices become established without adequate economic perspectives.

Theoretical work highlights AI’s role in shaping how knowledge evolves endogenously over time (Carnehl and Schneider, 2025) and how generative AI can reshape researchers’ incentives, leading them to strategically adjust the

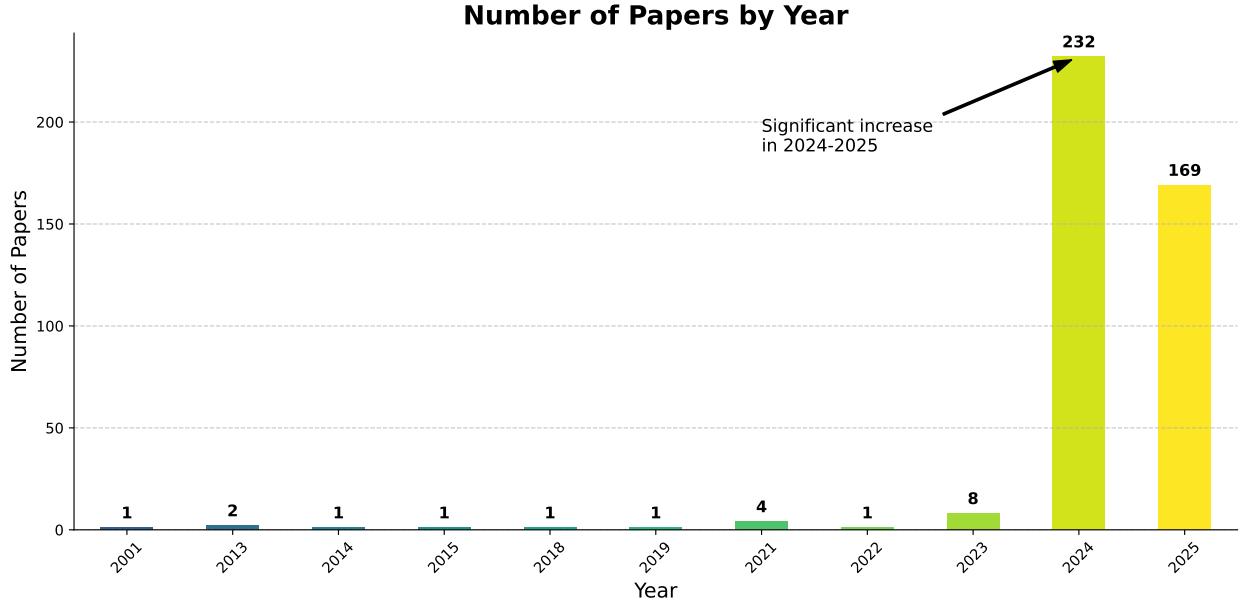


Figure 2: Applications of Agentic Workflows in Scientific Research by Year.

novelty of their work to leverage AI’s capabilities (Gans, 2025). Even at this early stage, these theoretical possibilities are beginning to manifest in practice, as LLMs are already reshaping research across multiple disciplines—from ideation to data analysis and manuscript preparation. While computer science currently dominates, applications are expanding into engineering, business, and healthcare. Within economics specifically, LLMs show significant promise: Korinek (2023) provides a systematic taxonomy of use cases ranging from experimental to highly useful across the research lifecycle, highlighting their potential as both assistants and collaborators. Complementing this, Cowen and Tabarrok (2023) offers practical guidance on integrating these unique tools into economic research and education. Together, these developments signal a paradigm shift: while still early, LLMs’ capacity to enhance productivity and expand methodological frontiers is increasingly evident, suggesting agentic workflows may soon become essential for bridging computational efficiency and innovations in economic research.

Economic research possesses unique characteristics that cannot be fully and efficiently captured by existing general agentic research frameworks. We argue that a domain-specific agentic workflow, one that integrates the experience of human economists, offers the best approach to leveraging AI technologies’ potential. As Athey (2025) notes, human economists act as product designers, market designers, process designers, designers of empirical analyses, designers of outcome measures, and designers of complex experiments. Consequently, the agentic workflow should be designed to support and enhance these diverse roles by automating routine tasks and supporting sophisticated analyses. This manuscript examines the development and integration of agentic workflows in economic research, focusing on how these systems can reshape research practices throughout the entire lifecycle. We explore seven critical applications of agentic workflows in economics: (i) Automating ideation with human inspirations; (ii) Facilitating dynamic, multimodal interaction with research materials; (iii) Enhancing literature review through semantic search and summarization; (iv) Streamlining data collection and preprocessing; (v) Supporting advanced modeling and experimental simulations; (vi) Assisting in result interpretation and visualization; (vii) Enabling reproducible and transparent research processes. Our methodology combines theoretical frameworks with practical implementations, leveraging state-of-the-art open-source LLMs and multimodal AI capabilities to create a blueprint for integrating agentic workflows into the economic research pipeline. Through detailed case studies and proof-of-concept demonstrations, we not only illustrate the current potential of these technologies but also address key methodological challenges and ethical considerations that arise in their implementation.

The remainder of this paper is structured as follows: First, we provide a review of existing literature on AI applications in economic research. We then present our methodology, detailing its architecture, components, and implementation considerations. Next, we demonstrate practical applications across different research stages, and conclude by discussing implications for economic methodology, limitations of current approaches, and directions for future research. This roadmap aims to facilitate the integration of agentic workflows into economic research, with the understanding that

these tools should augment rather than replace the creative and analytical capabilities that drive approaches in economic research.

2 Literature Review

This section reviews the existing literature on AI applications in scientific research, with a focus on agentic workflows and their potential to enhance economic research practices. We examine how LLMs and other AI technologies are being integrated across different stages of the research process, from ideation and writing to modeling, empirical analysis, result interpretation and replication—while maintaining human oversight at key decision points.

2.1 Ideation and Writing

Economic research has traditionally faced obstacles in the ideation and writing process, including literature fragmentation, cognitive overload, time constraints, and difficulty in synthesizing multidisciplinary insights. Research now shows that LLMs have reshaped these challenging aspects by improving productivity, creativity, and analytical capabilities across both professional and academic contexts. Notably, LLMs serve as collaborative partners that elevate the quality and efficiency of research workflows by reducing cognitive barriers and accelerating knowledge synthesis.

In professional settings, LLMs boost productivity in mid-level writing tasks (Noy and Zhang, 2023), and enhance creative output through AI-generated prompts and structured frameworks (Doshi and Hauser, 2024). Academic applications extend beyond simple writing assistance to fundamentally reshaping research methodologies—from streamlining literature reviews (Rahman et al., 2023) to enhancing survey design, content analysis, and modeling methodology (Bail, 2024). LLMs also work well in automating specialized academic classification tasks, as demonstrated in studies of Journal of Economic Literature (JEL) code assignment (Heikkilä, 2025).

Policy evaluation is another aspect where LLMs play an important role. LLMs demonstrate capability in drafting institutional reports (Biancotti and Camassa, 2023) and analyzing policy evaluations (Asatryan et al., 2024). Other applications reveal additional value in cryptocurrency research (Dowling and Lucey, 2023) and agricultural forecasting (Leigh, 2024), indicating LLMs' potential to process and generate insights from complex economic data.

Despite these advances, current applications remain primarily focused on static text generation rather than dynamic and iterative processes. At the same time, questions about verbal neutrality and accuracy persist. To solve these problems, we point out that the frontier of LLM-powered economic research lies in developing truly agentic systems capable of autonomously refining drafts, enhancing literature searches, and synthesizing insights from multiple data sources—moving beyond passive assistance toward active research partnership.

2.2 Modeling and Experimental Simulations

Economic research has traditionally faced challenges in modeling and experimental simulations, including high computational costs, limited sample diversity, and difficulty in scaling human-subject experiments. In response, LLMs have improved this domain by enabling cost-effective analyses of human behavior in economic contexts. These models effectively test economic assumptions, examine rationality, and simulate decision-making processes while addressing the limitations of conventional approaches. Research demonstrates that LLMs can replicate economic behavior across risk, time, and social preferences (Chen et al., 2023a; Ouyang et al., 2024) while mimicking human strategic reasoning in game-theoretic scenarios (Akata et al., 2023; Brookins and DeBacker, 2024). The AI-driven approaches offer cost-effective alternatives to traditional experiments, reproducing established behavioral results while enabling rapid iteration (Horton, 2023).

Agent-based simulations have further expanded modeling capabilities through collaborative LLM-based agents with consistent behavior patterns (Li et al., 2023b) and competitive frameworks for studying market dynamics (Zhao et al., 2024). Domain-specific agents provide new ideas into specialized economic decision-making compared to general-purpose models (Wen and Feng, 2025). Methodological innovations have established new research paradigms for economic and financial applications (Zheng et al., 2024; Durante et al., 2024; Tranchero et al., 2024; Caetano et al., 2025), with practical implementations in financial markets analysis (Penmetsa, 2024) and policy simulation through frameworks modeling Federal Open Market Committee (FOMC) meetings (Seok et al., 2024).

Despite these advances, current studies largely rely on manually curated prompts rather than fully agentic workflows capable of autonomously managing complete experimental cycles. This gap calls for developing self-directed, adaptive AI methodologies that can formulate hypotheses, execute simulations, analyze results, and iterate based on findings.

2.3 Data Analysis

Economic research has struggled with the analysis of unstructured data and large datasets, making it challenging to identify important patterns. LLMs excel in text mining, sentiment analysis, and predictive modeling across diverse economic domains. In consumer research, LLMs generate distributional survey responses that deepen understanding of preferences (Brand et al., 2024) and automate feedback on coding and statistical tasks (Jürgensmeier and Skiera, 2024). From the workforce perspective, the labor market analysis landscape has been reshaped through AI applications in knowledge-intensive consulting tasks (Dell'Acqua et al., 2023) and multi-country productivity analysis (Marioni et al., 2024). Workforce transformation research has advanced through frameworks that evaluate how LLMs reshape job tasks (Eloundou et al., 2024; Chen et al., 2024) and empirical studies of AI-powered assistants in customer support settings (Brynjolfsson et al., 2024).

More specifically, LLMs enhance empirical economic research through multiple channels. They boost productivity in professional tasks (Noy and Zhang, 2023), enable systematic analysis of corporate sustainability commitments from news articles (Bauer et al., 2024), and bridge the gap between human-like decision-making and rational economic behavior (Ross et al., 2024). These models work well as personalized decision aids (Kim et al., 2024) and enhance macroeconomic forecasting during high volatility periods (Allard et al., 2024), though concerns about training data leakage raise important methodological questions (Ludwig et al., 2025).

Financial applications demonstrate both the potential and limitations of LLM-powered analysis. While these models enable explainable financial time series forecasting (Yu et al., 2023), they face challenges in stock market prediction despite advanced prompting techniques (Xie et al., 2023). Domain-specific models like FinLlama offer improved financial sentiment analysis (Iacovides et al., 2024), with evidence that sophisticated LLMs can predict stock movements from news headlines (Lopez-Lira and Tang, 2024; Lefort et al., 2024).

Technological infrastructure like the Model Context Protocol by Anthropic and its implementation in constraint programming systems (Szeider, 2024) facilitate seamless integration between LLMs and structured data sources. Google's Recent Agent2Agent Protocol extends this capability by enabling autonomous agents to work together. However, most current applications mostly restricted in the IT communities, and economic researchers have yet to fully leverage the potential of agentic workflows.

2.4 Coding and Implementation

Economic research has historically faced technical barriers in coding and implementation, including steep learning curves for specialized econometric languages, difficulty maintaining reproducible codes, and challenges in efficiently implementing complex statistical models. LLMs have addressed these obstacles by serving as intelligent programming tools that improve code performance. These models help with pair programming, debugging assistance, and automating complex coding tasks across both mainstream and specialized environments.

Experimental studies demonstrate LLMs' impact on coding productivity, with systems like GitHub Copilot (Peng et al., 2023) assisting in code writing and debugging, and tools like CodeFuse boosting production by over 50% (Gambacorta et al., 2024)—though with the greatest benefits observed among junior programmers. Specifically, LLMs have shown benefits for specialized programming contexts, including niche econometric languages like *hansl* (Tarassow, 2023) and custom research assistants built on fine-tuned foundation models (Keleş and Bayraklı, 2024).

Other applications show LLMs' ability to generate and execute code that answers complex queries on temporal financial datasets (Lashuel et al., 2024), while architectural innovations in autonomous agent design (He et al., 2024) establish structures for more sophisticated coding assistance. Recent agentic Integrated Development Environments (IDEs), like Cursor and Windsurf, have also enhance the programming efficiency. Regardless of these advances, Economic research has yet to fully leverage end-to-end agentic workflows for computational tasks. The future potential lies in autonomous selecting the available codebase, adapting code to the task, and iteratively self-debugging. These advanced systems effectively transition from single-task assistance to fully autonomous coding agents, enabling automated hypothesis testing, dynamic model selection, and real-time debugging. Such advanced capabilities allow economists to enhance the efficiency and reproducibility of computational economic approaches while requiring more economists into the adapting and transition process.

2.5 Multimodal AI and Potential for Economics

Economic research faces several challenges in utilizing complex data types, including difficulty in integrating visual information with textual analysis, accurately interpreting graphical representations, and extracting structured insights from unstructured data. Multimodal AI systems—capable of processing and generating text, images, audio, and other data

types—help address issues in economic research tools, providing capabilities beyond text-only LLMs. These systems allow the combination of diverse data sources into analytical frameworks that enhance economic decision-making, though technical and methodological hurdles remain.

The architectural foundations for multimodal integration in economics are rapidly evolving, with cross-attention mechanisms and unified transformer models (Hertz et al., 2022; Mizrahi et al., 2023; Kapiton et al., 2024) enabling seamless processing across modalities. These technical advances support collaborative human-machine frameworks (Blasch et al., 2019) and enhance prediction model explainability (Rodis et al., 2024)—critical requirements for responsible economic analysis.

In financial applications, multimodal systems have shown effectiveness by combining ChatGPT’s inference capabilities with graph neural networks to enhance predictive accuracy (Chen et al., 2023b) and automating investment insight generation through fine-tuned models (Li et al., 2023a). The progression toward fully autonomous systems is evident in frameworks that transition from LLM-assisted to agent-enabled financial auditing (Schreyer et al., 2025) and multi-agent approaches for market anomaly detection (Park, 2024).

Governance and policy analysis also benefit from multimodal AI through enhanced decision support systems that help policymakers handle regulatory issues (Lorenz et al., 2023). Technical innovations like LlamaGen (Sun et al., 2024) expand generative capabilities beyond text to visual content, enabling economists to create data visualizations and graphical representations of complex economic concepts.

Despite these advances, economics has yet to fully leverage multimodal AI’s potential for automatically parsing, interpreting, and generating visual elements central to the discipline—time-series plots, econometric tables, and policy diagrams. Raising the performance of economic analysis by integrating visual and textual data forms a key direction that could influence how economists analyze complex datasets and communicate findings.

2.6 Toward Agentic Workflows in Economic Research: Summary and Research Gaps

Although there is growing interest in LLMs and AI-driven research methodologies, truly agentic workflows—where AI systems operate iteratively and autonomously across multiple research stages—remain rare in economics. While other fields, particularly computer science and software engineering, have pioneered self-directed AI agents capable of designing experiments, running analyses, and refining hypotheses based on outcomes, economics has been slower to adopt these approaches. Integrating agentic workflows into economic research could reduce friction in repetitive tasks and unlock new methodological efficiencies.

Among the most promising applications is the automated literature review, where AI agents can continuously refine search queries, synthesize new findings, and maintain dynamic, up-to-date literature landscapes. In addition, adaptive model-building systems could autonomously run, compare, and refine econometric or computational models (e.g., structural models, agent-based simulations, or GARCH variants in financial economics) with minimal human intervention. Context-aware data analysis offers another approach, moving beyond static, single-prompt sentiment analysis toward iterative, self-improving systems. These advanced systems incorporate real-time data updates, diagnostics, and adaptive modeling techniques (e.g., dynamically switching between linear and nonlinear models to improve accuracy or robustness). Moreover, end-to-end reproducibility could be greatly enhanced through automated documentation of code, data analysis, and iterative outputs, making replication more transparent.

Our review identifies two important gaps that must be addressed to advance agentic methodologies in economic research. The first gap lies in the lack of end-to-end agentic frameworks. Few studies have systematically explored AI pipelines that autonomously iterate through problem definition, model selection, data analysis, coding, and result interpretation. While isolated applications exist (e.g., LLM-assisted code generation and sentiment analysis), a cohesive and fully autonomous framework for economic research workflows remains underdeveloped. Such fragmentation restricts AI’s potential to improve economic methodology in a truly agentic manner. The second gap lies in the limited multimodal integration. Economic research heavily relies on visual representations such as tables, graphs, and diagrams, yet there is little research on multimodal AI for parsing, interpreting, or generating these elements. The ability to “read” figures and tables, extract key insights, and integrate them into an autonomous workflow remains underexplored, despite its potential to reshape how economists interact with data and communicate findings. Addressing these gaps could strengthen economic research methodologies, providing economists with more powerful, adaptive, and scalable analytical tools. The following sections of this paper aim to propose actionable frameworks for incorporating agentic workflows and multimodal AI capabilities, complementary to existing research processes while maintaining strategic human-in-the-loop oversight to preserve domain expertise.

3 Methodology

Building on the insights from our literature review, we propose a methodology based on agentic workflows for economic research that integrates LLMs and multimodal AI. Unlike traditional single-shot or prompt-based interactions, this methodology emphasizes *autonomous and iterative* (“*agentic*”) processes capable of handling a wide range of research tasks with minimal human supervision, including ideation, literature review, modeling, empirical analysis, result interpretation, and replication. The following sections outline the key phases of our proposed methodology, detailing how specialized agents are designed, how they coordinate in a workflow, and how continuous Human-in-the-Loop (HITL) oversight ensures quality and adaptability.

3.1 Agent Design

Each agent in the system is engineered to manage a clearly defined responsibility, making the research process more effective throughout the economic research lifecycle. The design is based on the following core principles:

Defined Responsibilities: Every agent is assigned a specific scope of focus within the economic research pipeline. For example, **Ideator** generates research questions on economic phenomena like market efficiency or policy impacts; **TopicCrawler** discovers relevant literature from repositories such as NBER, SSRN, and EconLit; **Estimator** runs empirical estimations using econometric methods (e.g., panel data analysis, instrumental variables); **DataCleaner** handles economic time-series analysis and outlier detection; **ModelDesigner** selects appropriate economic models (DSGE, VAR, structural equations); and **Proofreader** ensures manuscript quality, checking economic terminology and citation standards. This separation helps with specialized task execution with minimal overlap across the economic research workflow.

Inter-Agent Communication: Agents exchange necessary data in a structured Chain-of-Thought (CoT) that mirrors the economic research workflow. For instance, refined research questions from **Ideator** and **Refiner** flow into **Contextualizer** for theoretical mapping within economic paradigms (e.g., neoclassical, behavioral, or institutional economics), which then informs model specification by **Theorist** and **ModelDesigner** using appropriate economic frameworks (e.g., general equilibrium, game theory, or econometric specifications). Similarly, empirical outputs from **Estimator**, such as regression coefficients, elasticities, and statistical significance tests, are passed to **Validator**, **Diagnostic**, and **Optimizer** for robustness checks and sensitivity analyses, while interpretation outputs related to policy implications, welfare effects, and market dynamics are integrated by **Reporter** and **Proofreader** into cohesive economic narratives that align with established disciplinary conventions.

Error and Escalation Pathways: Each agent incorporates mechanisms to detect issues within its domain and either resolve them internally or escalate them. For example, if **Coder** encounters inconsistencies in econometric model translation (such as misspecified panel data models or incorrect instrumental variable implementations), it automatically flags the error for **Debugger**. **DataCleaner** can identify problematic outliers in macroeconomic time series and either apply appropriate statistical techniques (e.g., Hodrick-Prescott filtering, seasonal adjustments) or escalate to human review when facing structural breaks. Similarly, **Estimator** can detect heteroskedasticity, multicollinearity, or endogeneity issues in regression models and implement corrections like robust standard errors or two-stage least squares when appropriate. In parallel, if **Proofreader** detects major style differences with economic journal standards or factual discrepancies in theoretical frameworks (e.g., misattributed economic theories or outdated policy references), it alerts human experts for intervention.

Adaptive Mechanisms: Agents are designed with the flexibility to switch strategies or models if initial attempts are inadequate. For instance, if **GapFinder** identifies persistent literature gaps in macroeconomic theory or empirical finance, the system can automatically adjust search parameters or re-run queries using alternative methodologies such as different econometric specifications (e.g., switching from ARIMA to VAR models), employing heterogeneous agent models instead of representative agent frameworks, or shifting between neoclassical and behavioral economic paradigms. Similarly, when analyzing policy interventions, **ModelDesigner** can shift from reduced-form models to structural general equilibrium approaches if initial results fail to capture important cross-market effects, or implement different identification strategies (difference-in-differences, regression discontinuity, or instrumental variables) when causal inference challenges arise in empirical work.

The design and implementation of these agents are fundamentally guided by human expertise. Economic researchers define each agent’s responsibilities, knowledge boundaries, and interaction protocols based on established research methodologies and domain-specific requirements. This human-defined architecture ensures that the agents operate within appropriate parameters for economic analysis. The communication pathways between agents—whether sequential or parallel—are carefully structured by researchers to mirror the logical progression of economic research workflows. This deliberate design means that the system’s efficiency and effectiveness depend directly on the quality of human

expert input during the design phase. Furthermore, ethical considerations such as data privacy, citation integrity, and methodological transparency are embedded into agent protocols through human oversight. Potential ethical challenges in automated research processes are proactively addressed through careful system design and the implementation of human checkpoints.

3.2 Human in the Loop

Human experts are embedded at specific checkpoints throughout the workflow to guide and validate the autonomous processes. The pre-defined human oversight is the foundation of research quality and ethical integrity in economic research. The roles of human experts include:

Initial Review and Prioritization: During the Input & Sourcing Stage, economic researchers use a centralized dashboard to review and prioritize raw ideas, ensuring that only the most promising and relevant research questions proceed. This human filtering is essential for identifying topics with notable policy effects, theoretical contributions to economic paradigms, or potential to address socioeconomic challenges.

Iterative Feedback: In the Refinement Pipeline Stage, human economists provide real-time annotations and modifications to agent outputs, refining the research question's scope, theoretical grounding in established economic frameworks (e.g., neoclassical, behavioral, institutional), and methodological feasibility considering data availability and econometric requirements. This iterative human guidance ensures that research maintains disciplinary rigor and relevance to current economic debates.

Quality Control and Verification: Throughout empirical analysis, interpretation, and documentation, economists scrutinize various outputs (such as statistical results, causality claims, welfare analyses, draft manuscripts, and editorial reports) to validate their correctness, comprehensibility, and alignment with scholarly standards. This human verification is essential for detecting potential misinterpretations of economic phenomena. It also ensures the appropriate application of statistical methods and validates policy recommendations derived from the analysis.

Ethical Oversight and Bias Mitigation: Throughout all stages, human researchers actively monitor for potential ethical concerns. These include data privacy issues in sensitive economic datasets. Researchers also evaluate distributional implications of policy recommendations. Additionally, they identify algorithmic biases that might skew economic analyses along socioeconomic, racial, or gender lines. The ethical oversight is particularly critical when research involves vulnerable populations or has significant policy implications.

Methodological Validation: Human economists evaluate the appropriateness of selected econometric techniques, identification strategies, and theoretical models, ensuring they align with the research question and data characteristics. This includes assessing whether causal claims are justified, instrumental variables are valid, or whether general equilibrium effects are adequately captured.

Final Approval and Archiving: In the final stages of formatting, replication, and version control, researchers conduct necessary reviews and sign-offs to ensure that all components meet disciplinary standards, ethical guidelines, and replication requirements. The review includes examining data documentation, assessing code accessibility and clarity, and evaluating the comprehensiveness of sensitivity analyses, which are all critical components for producing trustworthy economic research.

The quality of these human checkpoints fundamentally determines the ultimate value of the research output. Without carefully designed human oversight protocols, autonomous research systems risk producing methodologically flawed analyses, ethically problematic conclusions, or economically irrelevant findings. The human-in-the-loop (HITL) framework thus serves as both a quality assurance mechanism and an ethical safeguard against potential misuse or misapplication of AI in economic research.

3.3 Workflow Coordination

The entire methodology is structured as an interconnected, multi-phase workflow. In this system, outputs from one phase serve as inputs to the next, ensuring progression from conceptualization to final replication. This coordination mirrors traditional economic research processes. At the same time, it acknowledges the complementary roles of AI agents and human experts. Key phases include:

Research Question Formulation and Initialization: Various specialized agents work together to generate, enrich, and refine research questions within economic paradigms. The workflow supports both autonomous ideation, where agents discover research questions from scratch by analyzing economic trends and literature gaps, and human-initiated ideation, where economists provide initial ideas that are systematically enriched and developed by the agent team. Human experts remain essential in this phase to evaluate the theoretical significance and policy relevance of the proposed questions.

Automated Literature Exploration: Multiple agents systematically discovers and synthesizes relevant economic literature, while dynamic management agents ensure that the literature remains current. However, these agents may occasionally hallucinate non-existent sources or misinterpret economic theories—similar to how human researchers might overlook key papers or misunderstand concepts. Therefore, specialized supervision agents with conservative parameters verify citations and theoretical interpretations, with human economists providing the final validation of the literature foundation.

Data Collection and Preprocessing: Specialized agents gather and prepare economic datasets (e.g., panel data, time series, cross-sectional surveys), followed by quality assurance agents that ensure robust and reproducible datasets. Human economists collaborate with these agents to address complex data issues such as structural breaks in macroeconomic time series or selection bias in microeconomic surveys that AI might not fully understand.

Model Specification, Implementation, and Empirical Estimation: A series of agents convert theoretical economic specifications into operational models (e.g., DSGE models, instrumental variable regressions, difference-in-differences designs), run empirical analyses, diagnose issues, and optimize performance. These agents may cause methodological errors or misspecify models, necessitating oversight by both specialized verification agents and human experts who understand the nuanced assumptions underlying economic models.

Interpretation and Reporting: Multiple agents collaborate to derive economic insights (e.g., elasticity interpretations, welfare implications, policy recommendations), compile the research manuscript, enforce quality assurance through detailed proofreading, and format the final document in compliance with economic journal submission guidelines. Human economists treat these agents as collaborative partners, critically evaluating their interpretations while acknowledging that both humans and AI can misinterpret statistical results or overstate causal claims.

Replication and Version Control: AI agents package, track, and securely archive all research assets to ensure that the entire project is fully replicable—a key requirement in modern economic research. Human economists maintain ultimate control over this process, determining which versions represent the authoritative research record.

Throughout this workflow, human economists maintain conclusive oversight of research quality and methodological integrity. They recognize that AI agents, like human research assistants, possess both strengths and limitations. By implementing specialized supervision agents with stricter verification parameters alongside human oversight, the workflow creates multiple layers of quality control. This partnership framework views AI systems not as perfect instruments but as imperfect research colleagues whose contributions demand the same rigorous evaluation applied to human-generated work.

4 Workflow Design and Implementation

This section presents a sample design and implementation of an agentic workflow system for economic research that follows the methodology outlined in Section 3. We describe a typical architecture, components, and operational mechanisms that enable collaborative research between AI agents and human economists, noting that actual implementations can vary based on researchers’ goals and design preferences. The following subsections elaborate on each stage of this example workflow.

4.1 Ideation

The ideation process in economic research presents challenges, including the need to navigate vast and rapidly expanding literature, identify meaningful gaps in knowledge, connect different theoretical frameworks, and formulate questions with both academic precision and policy relevance. To address these difficulties, we employ *agentic workflows* that enhance the efficiency and effectiveness of research question formulation. This workflow leverages a suite of specialized, semi-autonomous agents—each with a well-defined role and triggering mechanism—to identify emerging trends, scan literature, and synthesize information at a scale beyond human capacity. By integrating HITL checkpoints for oversight and quality assurance, the system combines computational efficiency with domain expertise, reducing the time and cognitive load traditionally required for ideation while maintaining research integrity. The following subsections describe the agents and outline their respective responsibilities. They also explain how these agents work together to generate and refine candidate research questions. The resulting questions are not only theoretically grounded but also aligned with real-world research needs.

4.1.1 Specialized Agents

The ideation phase employs a coordinated network of agents, each responsible for distinct yet complementary tasks within the research question formulation process. These agents operate in a sequential-parallel architecture, sharing

information through standardized data structures while maintaining independent processing capabilities. Together, they form a system that spans from broad trend identification to precise research question formulation, with human oversight integrated at strategic checkpoints. The following agents constitute the core components of this ideation ecosystem:

TrendSurfer identifies emerging or trending topics in real time by scanning various news outlets, social media platforms, blogs, policy briefs, etc. It is automatically activated at preset intervals or can be triggered on-demand during researcher-led brainstorming sessions.

TopicCrawler gathers preliminary academic literature from open-source repositories such as JSTOR, SSRN, arXiv, and NBER to build an initial knowledge base. It generates a structured literature database with basic metadata that serves as the foundation for deeper analysis. This agent runs on a set schedule or can be manually initiated by economists who require broad literature coverage. **TopicCrawler** works in close coordination with **ScholarSearcher** and provides its initial literature findings to **Ideator** for concept generation.

ScholarSearcher executes sophisticated academic queries across premier research databases including Web of Science, Scopus, and EconLit. It accesses subscription-based repositories and produces standardized research data with removed duplicates, rankings, and organized tags. The agent is triggered when detailed research is needed following **TopicCrawler**'s initial scan. **ScholarSearcher** collaborates with **TopicCrawler** and feeds organized scholarly literature directly to **Ideator**, enabling better coverage of peer-reviewed research.

GreyScout expands the search beyond peer-reviewed publications by scanning grey literature, including working papers, policy briefs, and conference proceedings from institutions like the IMF and World Bank. It creates a non-academic literature database with relevance scoring that captures emerging ideas not yet formalized in academic journals. This agent activates periodically or in response to new uploads in relevant repositories. **GreyScout** complements **ScholarSearcher**'s academic focus and provides alternative perspectives to **Ideator**, ensuring a balanced view of both established and emerging knowledge.

Ideator aggregates insights from both human researchers and the sources discovered by other agents to produce initial ideas, hypotheses, and key concepts. It generates potential research directions based on the information gathered throughout the system. The agent activates whenever new information emerges—either from scheduled scans or researcher inputs—to maintain a constant flow of potential research ideas. **Ideator** receives data from **TopicCrawler**, **ScholarSearcher**, and **GreyScout**, and subsequently feeds its generated ideas to **Refiner** for evaluation and narrowing.

Refiner evaluates the ideas generated by **Ideator**, filtering out redundancies, ensuring conceptual coherence, and narrowing broad topics into well-defined research questions. It produces focused research questions derived from initially broad concepts. The agent engages automatically whenever new or updated ideas arrive from **Ideator**, often incorporating human feedback or similarity checks during its refinement process. **Refiner** processes **Ideator**'s output and forwards its refined questions to **Contextualizer** for theoretical framing.

Contextualizer adds depth to emerging questions by mapping them against established economic theories and highlighting relevant policy debates. It creates contextualized research questions with clear theoretical and policy relevance that situate the inquiry within the broader academic discourse. This agent is triggered after gap analyses, debate-detection outputs, or by researcher request. **Contextualizer** processes **Refiner**'s output and passes its contextualized questions to **Finalizer** for synthesis and prioritization.

Finalizer aggregates and synthesizes the refined questions, ensuring alignment with project objectives and validating them against related literature. It produces a prioritized shortlist of research questions ready for final selection that represents the main idea of the entire ideation process. The agent is generally initiated by researchers seeking to finalize the research question set after iterative refinements. **Finalizer** receives input from **Contextualizer** and presents its final questions to human researchers for ultimate decision-making, completing the ideation cycle.

4.1.2 Agentic Workflows with Human in the Loop

The above agents function within a multi-stage process, each stage involving both automated actions and researcher oversight.

Input & Sourcing Stage Human experts can propose an initial research question or identify broad areas of interest. **TrendSurfer**, **TopicCrawler**, **ScholarSearcher**, and **GreyScout** independently conduct literature searches, collecting both peer-reviewed and grey literature. Researchers review the aggregated output in a centralized dashboard, adjusting search parameters or prioritizing particular topics. This *HITL checkpoint* ensures alignment with specific research objectives.

Refinement Pipeline Stage The Ideator synthesizes all incoming data (researcher prompts, existing literature), creating a wide array of potential questions or hypotheses. The Refiner evaluates these ideas for clarity and scope, removing redundancies and identifying overlapping concepts. Researchers provide domain expertise, clarifications, and real-time annotations through an interactive interface, ensuring that the evolving questions remain both theoretically robust and practically meaningful.

Integration & Final Vetting Stage The Contextualizer situates each refined question within relevant theoretical frameworks, policy debates, and the existing body of knowledge. The Finalizer compiles a shortlist of potential research questions, verifying their alignment with the project's strategic goals. Researchers critically assess the Finalizer's output, merging or discarding questions as necessary. The selected questions form the foundation for subsequent phases of the research.

Human-in-the-Loop Checkpoints Although a large portion of literature retrieval and preliminary analysis is automated, critical decisions and domain-specific insights continue to be guided by human experts. Researchers can refine agent parameters (e.g., adding new keywords, broadening or narrowing search criteria). Manual reviews ensure that the discovered literature and proposed topics are of high academic relevance and not driven by algorithmic biases, and Researchers determine whether the emerging questions match institutional or personal research agendas before proceeding to deeper investigation.

By integrating specialized agents with structured human oversight, the workflow reduces the time spent on initial literature screening, trend identification, and idea generation. It also mitigates risks associated with incomplete searches or overly broad topics. The methodology thus serves as a solid base, ensuring that subsequent analytical steps begin with a set of refined, contextually grounded, and strategically aligned research questions.

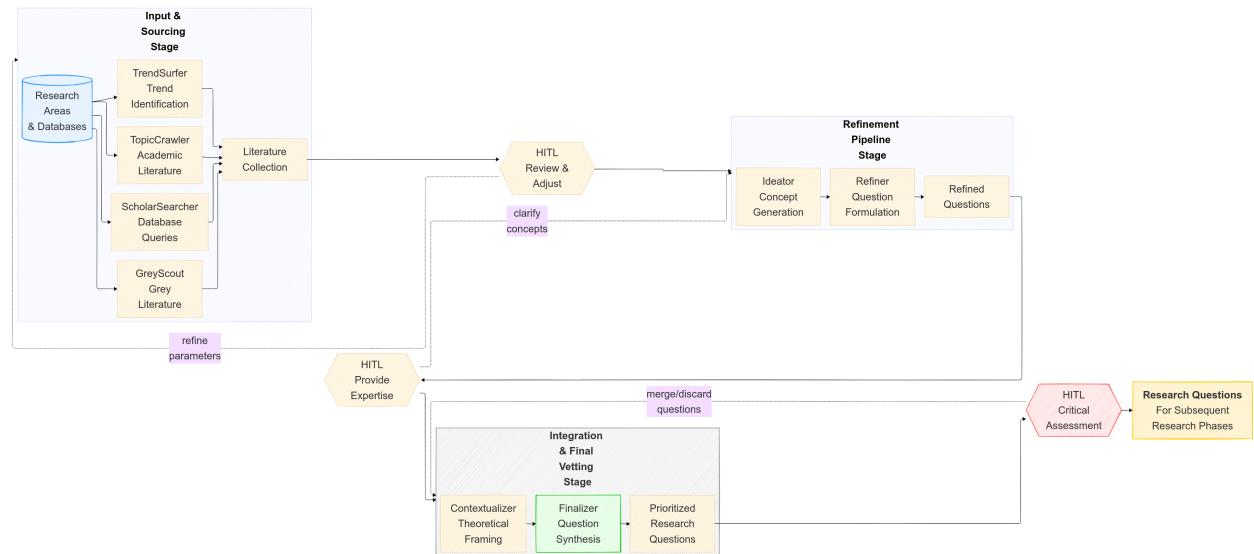


Figure 3: Agentic Workflow of Ideation in Economic Research

4.2 Automated Literature Review and Synthesis

This phase systematically finds, examines, and combines relevant literature using a network of specialized agents. Advanced natural language processing techniques and domain-specific heuristics improve the accuracy and relevance of the literature, while real-time HITL integration keeps the literature base aligned with the evolving research agenda. Current commercial products include ResearchRabbit, Connected Papers, SciSpace, Elicit, Litmap, OpenRead, Scholarcy, etc.

4.2.1 Specialized Agents

These agents form an automated literature review pipeline, streamlining the process of summarizing, analyzing, organizing, and tracking academic research. They help extract insights, identify research gaps, and maintain a structured knowledge base tailored for economic research.

InsightSummarizer functions as a concise knowledge extractor for economic papers. Its primary role is to distill key theoretical frameworks, econometric findings, and policy implications from collected studies. The agent takes input from raw paper PDFs, preprints, and published articles sourced from economic repositories and databases. It produces structured summaries highlighting methodological approaches, economic models employed, and empirical results with statistical significance. **InsightSummarizer** activates immediately after **TopicCrawler** retrieves new batches of economic papers or when researchers explicitly request overviews of specific economic topics. It integrates closely with **GapFinder** by providing processed summaries that serve as input for gap analysis, and with **KnowledgeWeaver** by contributing distilled knowledge points to the literature graph.

PaperDecomposer serves as a structural analyst for economic research papers. Its role involves segmenting economic studies into their core components—research questions, theoretical foundations, econometric methodologies, empirical results, and limitations. The agent processes full-text papers and supplementary materials, including statistical appendices and mathematical proofs. It outputs standardized decompositions of each study, extracting economic models, regression specifications, and causal identification strategies. **PaperDecomposer** operates on-demand when researchers require deeper analysis of methodological approaches or when comparing similar economic studies. It collaborates with **InsightSummarizer** by providing detailed structural components that enrich summary content, and feeds **GapFinder** with methodological details that help identify research opportunities in economics.

GapFinder functions as a research opportunity detector within economic literature. Its role is to identify underexplored economic phenomena, methodological limitations, and contradictory findings across studies. It takes input from processed summaries and paper decompositions, as well as citation networks and publication metadata. The agent produces gap analyses highlighting promising research directions, methodological innovations needed, and potential contributions to economic theory. **GapFinder** activates after **InsightSummarizer** completes processing batches of literature or when economists highlight specific uncertainties in existing research. It integrates with **KnowledgeWeaver** by providing gap insights that shape the evolution of research questions, and with **TrendTracker** by identifying emerging areas requiring monitoring.

CiteKeeper acts as the bibliographic management system for economic research. Its role involves maintaining reference information and facilitating proper attribution practices. The agent ingests metadata from published economic papers, working papers, and conference proceedings, including author affiliations, journal impact factors, and citation counts. It produces standardized citation entries in economic journal formats (AEA, JEL, etc.), manages DOI information, and generates formatted bibliographies. **CiteKeeper** updates continuously as new economic literature enters the system, with particular attention to version tracking for working papers. It connects with all other agents by providing normalized reference data, particularly supporting **TrendTracker** with citation metrics and **KnowledgeWeaver** with bibliographic relationships.

TrendTracker serves as the field monitoring system. Its role involves identifying emerging research directions, methodological innovations, and shifts in theoretical paradigms. The agent monitors economic journal publications, working paper series (NBER, CEPR, etc.), and conference proceedings, while tracking citation patterns and social media mentions of economic research. It produces trend reports, alerts on high-impact new studies, and visualization of emerging economic topics. **TrendTracker** operates continuously with customizable alert thresholds based on citation velocity and attention metrics. It feeds **KnowledgeWeaver** with trend information that shapes the literature graph, while providing **InsightSummarizer** with prioritization signals for what papers require immediate attention.

KnowledgeWeaver functions as the integrative synthesis engine for economic literature. Its role is to construct maps of economic knowledge domains, showing theoretical lineages and empirical contradictions. The agent processes all outputs from other agents, including summaries, decompositions, gap analyses, citation data, and trend reports. It produces interactive literature graphs visualizing schools of economic thought, methodology clusters, and conceptual relationships, while maintaining detailed research notes. **KnowledgeWeaver** activates on-demand for literature reviews or automatically during quarterly research planning cycles. It integrates with all other agents by consolidating their outputs into a cohesive knowledge structure, particularly informing **GapFinder** about system-level patterns that might reveal new research opportunities.

4.2.2 Agentic Workflows with Human-in-the-Loop

The literature discovery and synthesis phase is organized into multiple interconnected stages that involve real-time collaboration between AI agents and human researchers. At each stage, researchers guide, validate, and refine the automated outputs, ensuring that all findings are both academically rigorous and aligned with evolving project objectives.

Literature Gathering Stage In the initial stage, **TrendTracker** and **CiteKeeper** continuously search for, aggregate, and update new literature in the field. **TopicCrawler** retrieves broad sets of relevant studies from major databases, while **InsightSummarizer** generates concise overviews of key findings. Researchers then review initial batches of

retrieved papers and summaries through an interactive dashboard, refining search parameters and excluding irrelevant topics at a dedicated *HITL checkpoint*.

Summarization and Gap Detection Stage Once literature has been collected, PaperDecomposer segments each study into discrete structural components, enabling deeper analysis of its research question, methodology, and findings. GapFinder then examines study findings to identify methodological gaps and underexplored topics, while KnowledgeWeaver updates the literature graph to reflect emerging themes and overlapping areas. At this stage, researchers engage with interactive summaries and gap analyses, merging or discarding duplicates and prioritizing directions for deeper inquiry, ensuring that the most relevant insights are carried forward.

Synthesis and Integration Stage With a refined literature base, KnowledgeWeaver compiles updated research notes and thematic clusters, providing a holistic view of how different studies connect or contradict each other. CiteKeeper finalizes reference lists, ensuring standardized citation formats and seamless integration with external reference managers. Researchers critically evaluate the synthesized literature map, validate key insights, and confirm the alignment of findings with the overarching research focus. Any newly identified gaps are flagged for further investigation, maintaining a dynamic and evolving understanding of the field.

Human-in-the-Loop Role Throughout this phase, researchers work with interactive dashboards to review synthesized summaries, gap analyses, and literature graphs. They annotate and validate key findings while refining identified research gaps to ensure that agent outputs remain both accurate and relevant. The literature management dashboard facilitates ongoing curation, annotation updates, and graph adjustments, guaranteeing that new insights are promptly integrated into the research plan and that the system's evolving perspectives remain aligned with the project's goals.

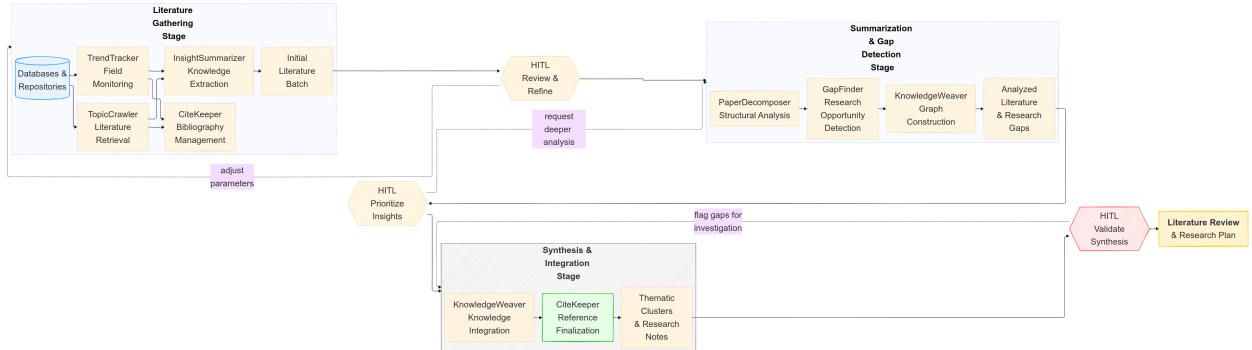


Figure 4: Agentic Workflow for Literature Review and Synthesis in Economic Research

4.3 Model Specification and Calibration

This phase centers on establishing a rigorous theoretical foundation, expressing it in mathematical or computational form, and calibrating model parameters to match real-world data and established economic principles. A coordinated set of specialized agents—Theorist, ModelDesigner, and Calibrator—collaborate under continuous human oversight, producing models that combine theory and real-world observations.

4.3.1 Specialized Agents

These agents form a structured framework for developing economic models, from theoretical formulation to mathematical implementation and calibration. Each agent handles conceptual soundness, logical consistency, and empirical relevance.

Theorist functions as the conceptual architect for economic models. Its primary role is to establish the theoretical foundation by selecting appropriate economic paradigms, defining assumptions, and outlining functional relationships between variables. The agent processes inputs from research questions, literature reviews, and human-specified constraints about economic phenomena being studied. It produces theoretical frameworks with clearly articulated economic assumptions, behavioral mechanisms, and expected relationships among variables. Theorist activates when preliminary research questions are sufficiently refined or when economic researchers initiate the model development phase. It integrates closely with KnowledgeWeaver from the literature review phase by incorporating synthesized theoretical insights, and provides its theoretical framework directly to ModelDesigner for mathematical formalization, establishing a conceptual foundation for subsequent model development.

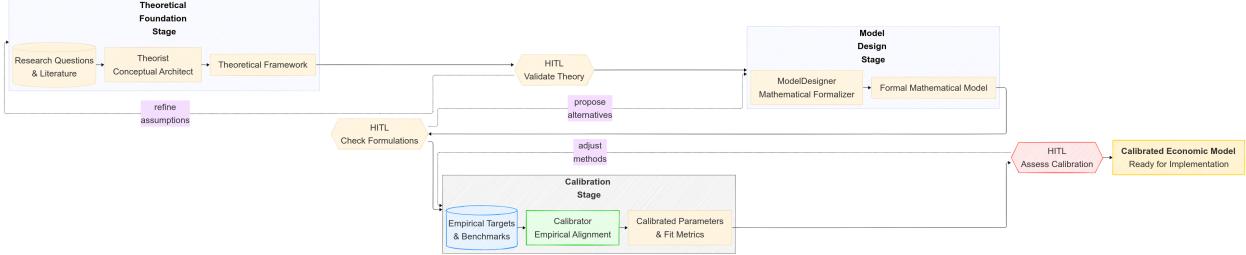


Figure 5: Agentic Workflow for Model Specification and Calibration in Economic Research

ModelDesigner serves as the mathematical formalizer for economic theories. Its role involves translating theoretical constructs into precise mathematical structures such as utility functions, production technologies, or market equilibrium conditions. The agent processes the theoretical framework from **Theorist**, along with model specification requirements and methodological preferences from researchers. It outputs formal mathematical models including equations (difference/differential, recursive, or simultaneous), parameter definitions, and computational implementation guidelines. **ModelDesigner** activates immediately after **Theorist** finalizes the theoretical framework or when researchers request alternative mathematical formulations of existing theories. It collaborates with both **Theorist** by translating its conceptual insights and with **Calibrator** by providing the formal structure that requires parameterization, connecting theory and implementation.

Calibrator functions as the empirical alignment specialist for economic models. Its role involves determining parameter values that ensure models reproduce key empirical facts or stylized economic phenomena. The agent takes inputs from the formal model structure produced by **ModelDesigner**, empirical targets from the literature, and preliminary datasets provided by researchers. It generates calibrated parameter sets, goodness-of-fit metrics comparing model behavior to empirical targets, and sensitivity analyses showing how parameter variations affect model outcomes. **Calibrator** activates once **ModelDesigner** completes the formal model structure and preliminary data or benchmarks become available. It integrates with **ModelDesigner** by operationalizing its mathematical framework, and connects with **Validator** in the empirical estimation phase by providing baseline calibrated parameters that can be compared with estimated values, ensuring model consistency across theoretical and empirical stages.

4.3.2 Integrated Workflow with HITL

The model development process consists of three key stages: formulating the theoretical foundation, designing the model structure, and calibrating parameters. At each stage, specialized agents collaborate with human researchers to maintain accurate theory, sound math, and empirical support.

Theoretical Foundation Stage In the initial stage, **Theorist** formulates the economic foundation by defining assumptions, selecting functional forms, and identifying critical constructs. It integrates human-initiated insights with automated literature scans, incorporating both established and emerging theoretical viewpoints. Researchers review the proposed framework through an interactive interface, validating its coherence with existing theories and project objectives. They refine assumptions and select alternative theoretical constructs as necessary, verifying the model's alignment with the intended research direction.

Model Design Stage Building on the theoretical framework, **ModelDesigner** translates validated concepts into a structured model by specifying equations, defining variables, and outlining computational algorithms. It identifies the essential components needed to capture the underlying economic dynamics. Human experts validate this theory-to-model translation, checking for consistency and mathematical soundness. Researchers annotate model components, refine variable definitions, and propose alternative formulations to enhance the representation of economic mechanisms.

Calibration Stage With the model structure in place, **Calibrator** fine-tunes its parameters using preliminary or benchmark data, running simulations to evaluate how well the model replicates real-world observations. It generates diagnostic outputs, including sensitivity analyses and goodness-of-fit metrics. Researchers assess calibration outcomes via a dashboard, comparing simulated results with empirical or theoretical benchmarks. Through iterative refinement, they adjust calibration methods and ensure that the final parameterization aligns with both theoretical expectations and empirical evidence.

4.4 Data Collection and Preprocessing

This phase focuses on systematically gathering, cleaning, and preparing economic data. These data include time series, panel data, unstructured text, and data from alternative sources (e.g., satellite imagery, social media feeds). By leveraging specialized agents with distinct roles, the workflow improves data quality, transparency, and reproducibility. Crucially, human experts remain in the loop through interactive feedback, guiding and validating each step of the process.

4.4.1 Specialized Agents

These agents collectively form an automated data processing pipeline, facilitating dataset discovery, retrieval, cleaning, integration, validation, and documentation. Each agent has a specific function, from identifying relevant data sources to maintaining reproducibility, enabling a structured and transparent workflow for research.

DataScout functions as the economic data discovery specialist. Its primary role is to identify and evaluate relevant datasets that match the research requirements for economic analysis. The agent scans academic databases, APIs, and specialized repositories (FRED, Bloomberg, World Bank, OECD, Eurostat) to locate both conventional economic indicators and alternative data sources. It processes inputs from research questions, model specifications, and researcher-defined data requirements. DataScout produces dataset inventories with relevance scores, source reliability ratings, access requirements, and update frequencies for economic time series, cross-sectional, and panel data. It activates either through scheduled periodic scans of data repositories or when manually initiated by researchers exploring new economic topics or requiring updated information. It integrates with **DataCollector** by providing prioritized dataset lists for acquisition, and with **DocuAgent** by supplying metadata about source characteristics, documenting the data sources in economic research.

DataCollector serves as the acquisition and standardization system for economic datasets. Its role involves retrieving identified datasets while maintaining access compliance and standardizing formats across sources. The agent processes targeted dataset URLs, API endpoints, and access credentials from **DataScout**, along with researcher-specified collection parameters. It outputs standardized raw datasets with harmonized formats addressing international differences in time zones, currencies, units of measurement, and periodicity commonly found in economic data. **DataCollector** activates immediately after **DataScout** compiles its inventory of relevant sources or upon direct researcher request for specific economic series. It works in coordination with **DataScout** by executing its acquisition recommendations, and with **DataCleaner** by delivering consistently formatted raw datasets, establishing the foundation for subsequent cleaning operations in the economic data pipeline.

DataCleaner functions as the quality control specialist for economic datasets. Its role involves identifying and resolving data quality issues while preserving the integrity of economic information. The agent processes raw datasets from **DataCollector**, along with domain-specific cleaning rules and researcher-specified quality thresholds. It produces processed datasets with documentation of all modifications, including missing value treatments (using appropriate methods for economic time series like interpolation or multiple imputation), outlier handling, and duplicate removal. **DataCleaner** activates following successful data collection or when researchers identify quality issues in existing datasets. It integrates with **DataCollector** by processing its raw outputs, and with **DataIntegrator** by providing cleaned, individual datasets ready for merging, ensuring that subsequent economic analyses begin with reliable data.

DataIntegrator serves as the dataset consolidation engine. Its role involves merging disparate data sources into coherent, analysis-ready datasets while resolving structural heterogeneity. The agent processes multiple cleaned datasets from **DataCleaner**, along with researcher specifications for desired integration outcomes. It produces unified datasets with harmonized variable names, aligned time indices for economic time series, consistent cross-sectional identifiers, and optimized data structures for analytical efficiency. **DataIntegrator** activates once **DataCleaner** completes processing individual datasets or when researchers require a combination of disparate economic data sources. It works with **DataCleaner** by building upon its quality-assured outputs, and with **FeatureEngineer** by providing integrated datasets ready for feature creation, facilitating sophisticated economic analyses that require multiple data sources.

FeatureEngineer functions as the variable creation specialist for economic analysis. Its role involves developing theoretically-grounded derived variables that enhance analytical capabilities. The agent processes integrated datasets from **DataIntegrator**, along with economic theory specifications and researcher requirements for analytical features. It outputs enriched datasets containing derived economic indicators (e.g., real values from nominal, financial ratios, growth rates, cyclical components), transformed variables for statistical compliance, and dimensionality reductions for high-dimensional economic data. **FeatureEngineer** activates upon researcher request for specific data analysis or when model specifications require particular variable forms not present in the raw data. It integrates with **DataIntegrator** by enhancing its consolidated datasets, and with **ValidationSuite** by providing feature-rich

datasets ready for quality verification, supporting sophisticated econometric modeling with appropriately constructed variables.

ValidationSuite serves as the statistical verification system for economic datasets. Its role involves ensuring that prepared data meet essential quality and statistical requirements for valid economic analysis. The agent processes feature-enhanced datasets from **FeatureEngineer**, along with predefined validation rules and economic benchmarks. It produces validation reports detailing statistical properties (stationarity, normality, heteroskedasticity), variable correlations, benchmark comparisons against established economic facts, and recommendations for additional data processing if needed. **ValidationSuite** activates once data preprocessing is complete or periodically during updates to ensure ongoing data integrity. It works closely with **FeatureEngineer** by validating its derived variables, and with **DocuAgent** by providing statistical assessment reports, ensuring that economic analyses are built on data that meet necessary statistical assumptions.

DocuAgent functions as the documentation specialist. Its role involves creating detailed metadata and maintaining processing records to ensure research transparency and reproducibility. The agent collects information from all preceding data agents, including source characteristics, processing steps, and quality assessments. It generates detailed data dictionaries with economic variable definitions, units, and sources; transformation logs documenting all data analyses; and quality reports highlighting potential limitations or special considerations for economic interpretation. **DocuAgent** runs continuously throughout the data processing workflow, updating documentation with each modification or on scheduled intervals. It integrates with all other agents by centralizing their metadata and processing information, and connects with **ReproducibilityAgent** by providing complete documentation needed for replication packages, supporting transparent and credible economic research practices.

ReproducibilityAgent serves as the replication assurance system for economic research. Its role involves maintaining complete replication pathways from raw inputs to final datasets used in analysis. The agent processes complete workflow information, including code versions, random seeds, and processing sequences from all data pipeline steps. It outputs versioned preprocessing pipelines enabling the exact reproduction of economic datasets, environment specifications detailing all computational requirements, and audit trails documenting each modification throughout the data preparation process. **ReproducibilityAgent** activates after dataset updates or upon researcher request for replication packages prior to publication. It works closely with **DocuAgent** by incorporating its documentation into replication materials, and connects with modeling and estimation agents by providing them with precisely documented datasets, ensuring that economic research meets increasingly stringent standards for computational reproducibility.

4.4.2 Integrated Workflow with HITL

The data preparation process consists of three key stages: integrating data sources, preprocessing and cleaning, and ensuring quality assurance and documentation. At each step, specialized agents work alongside researchers to validate data reliability, enhance analytical operations, and maintain transparency in the workflow.

Data Source Integration Stage Researchers review identified and collected datasets through a centralized dashboard, where they can manually adjust source priorities, verify access protocols, and flag data sources requiring special handling or additional review. This oversight ensures that all inputs align with the project's objectives and that data discovery remains transparent and reliable.

Data Preprocessing and Cleaning Stage During this stage, researchers interact with intuitive tools that display data quality metrics and transformation logs generated by **DataCleaner** and **DataIntegrator**. They also access options for parameter adjustments and feature construction via **FeatureEngineer**, while anomalies or discrepancies detected by **ValidationSuite** are highlighted for review. Human experts validate or override automated decisions, suggest alternative cleaning strategies, and propose additional derived variables, ensuring that the final dataset remains both accurate and aligned with domain-specific analytical needs.

Quality Assurance and Documentation Stage To maintain rigorous standards, **ValidationSuite** and **DocuAgent** generate reports detailing statistical tests, economic validation checks, metadata documentation, and version-control logs. Researchers review these reports in a dedicated quality dashboard, confirming that all modifications are transparent, reproducible, and meet the study's standards. When necessary, they request additional tests, annotate findings, or roll back changes via **ReproducibilityAgent**, preserving the integrity and traceability of the entire data preparation process.

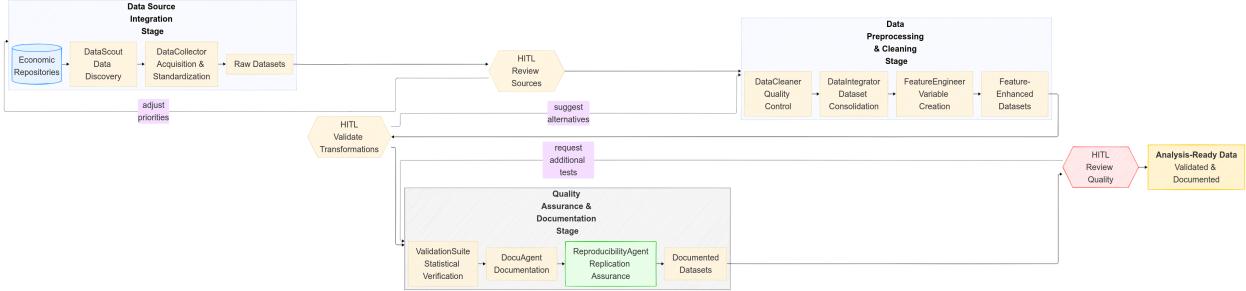


Figure 6: Agentic Workflow for Data Collection and Preprocessing in Economic Research

4.5 Model Implementation and Debugging

This phase translates theoretical model specifications into a functioning system through a coordinated network of specialized agents. Each agent handles a distinct but interdependent task, while human oversight is embedded throughout to maintain quality, traceability, and alignment with theoretical expectations.

4.5.1 Specialized Agents

These agents form an automated code development and validation pipeline, helping researchers implement economic models correctly. Each agent takes responsibility for generating, monitoring, and refining the codebase while incorporating human oversight for quality control.

Coder functions as the implementation specialist for economic models. Its primary role is to translate mathematical specifications into executable code that accurately captures the underlying economic theory. The agent processes formal mathematical models from **ModelDesigner**, algorithmic requirements, and researcher-specified programming preferences (language, frameworks, libraries). It produces structured codebases with modular implementations of economic equations, simulation routines, estimation procedures, and user interfaces for parameter adjustments. **Coder** activates upon receiving finalized model specifications from **ModelDesigner** or when researchers request implementation updates to reflect theoretical refinements. It integrates with **ModelDesigner** by implementing its mathematical framework, with **Logger** by marking code generation events, and with **Debugger** by automatically passing new code implementations for verification, maintaining theoretical integrity throughout the implementation process.

Debugger serves as the code quality assurance specialist. Its role involves identifying and resolving implementation errors while preserving the model's theoretical foundations. The agent analyzes code produced by **Coder**, error logs, execution traces, and theoretical constraints that must be satisfied. It generates diagnostic reports detailing logical inconsistencies, numerical instabilities, and mathematical errors; proposed fixes with theoretical justifications; and validation tests confirming correct behavior. **Debugger** activates whenever new code becomes available from **Coder** or when errors are detected during execution by **Logger** or **TestSuite**. It works closely with **Coder** by providing implementation feedback, with **Logger** by retrieving detailed error information, and with **TestSuite** by validating that corrections satisfy both theoretical requirements and empirical test cases.

Logger functions as the monitoring system for model development. Its role involves maintaining complete records of all implementation activities and system behaviors for traceability and transparency. The agent captures execution flows, system states, variable values, and agent interactions across the implementation pipeline. It produces three types of outputs: (i) structured, time-stamped logs that categorize events based on their severity and context; (ii) audit trails that record code changes and parameter updates over time; and (iii) periodic summaries that highlight recurring patterns or detect anomalies. **Logger** operates continuously throughout the implementation process, capturing information from all other agents in real-time. It supports **Debugger** by providing detailed context for error diagnosis, assists **TestSuite** with execution monitoring, and feeds **DocuAgent** with development histories, ensuring that every aspect of model implementation is traceable for research transparency.

TestSuite serves as the validation framework for model implementations. Its role involves systematically verifying that the coded model behaves according to theoretical expectations across relevant parameter spaces. The agent processes model specifications, known analytical results, stylized economic facts, and edge-case scenarios developed by researchers. It produces test cases covering theoretical properties (budget constraints, market clearing, steady-state behaviors); numerical stability assessments under various parameter configurations; and regression tests ensuring new

changes preserve previous validations. **TestSuite** activates after **Debugger** confirms basic code correctness or when researchers need verification of specific economic properties. It connects with **Coder** and **Debugger** by providing immediate feedback on implementation issues, and with **Optimizer** by confirming that performance improvements preserve theoretical validity.

Optimizer functions as the performance enhancement specialist for economic simulations. Its role involves improving computational efficiency while preserving numerical accuracy in economic models, particularly for large-scale DSGE models, agent-based simulations, or computationally intensive estimations. The agent analyzes code structure, execution profiles, memory usage patterns, and performance bottlenecks across the estimation workflow. It delivers optimized code with algorithmic improvements, parallelization strategies for multi-core processing, memory usage refinements, and numerical approximation techniques. **Optimizer** activates after **TestSuite** confirms model correctness or when researchers identify performance constraints limiting model complexity or resolution. It collaborates with **Coder** by suggesting implementation improvements, with **TestSuite** by ensuring that optimizations maintain theoretical consistency, and with **BatchRunner** by enabling parameter space exploration through enhanced performance.

BatchRunner serves as the systematic experimentation engine for economic models. Its role involves coordinating large-scale simulation runs across parameter spaces to generate results for analysis. The agent processes model configurations, parameter ranges for sensitivity analysis, shock specifications for impulse responses, and computational resource constraints. It produces organized simulation outputs including parameter sweep results, Monte Carlo simulation statistics, impulse response functions for macroeconomic variables, and comparative analysis across model variants. **BatchRunner** activates upon researcher request for model analysis or when **Calibrator** requires validation of parameter sensitivity. It interfaces with **Optimizer** to ensure efficient execution of computation-intensive tasks, with **VersionManager** to maintain clear information of which model version generated which results, and with **ResultsInterpreter** in the empirical analysis phase by providing structured simulation outputs.

VersionManager functions as the code sources and lifecycle specialist for economic model implementations. Its role involves maintaining version control, facilitating collaboration, and making model iterations reproducible. The agent tracks code changes, parameter modifications, branch development, and deployed versions. It produces versioned codebases with clear change history, integrated development environments for collaborative model construction, deployment pipelines for production use, and reproducible model packages linked to specific research outputs. **VersionManager** operates continuously throughout the model development lifecycle, automatically tracking changes and coordinating merges of parallel development. It connects with all implementation agents by providing version context for all operations, and particularly supports **ReproducibilityAgent** by ensuring that exact model versions corresponding to published results can be precisely recreated.

DocuAgent serves as the technical documentation specialist for economic model implementations. Its role involves creating documentation of model code, algorithms, and technical specifications that complement theoretical descriptions. The agent collects implementation decisions, code structures, parameter definitions, and usage instructions from all implementation phases. It generates detailed code documentation with economic interpretation of algorithms; technical manuals explaining model operations; API specifications for model extension or integration; and methodology appendices for research papers explaining implementation details. **DocuAgent** activates after development milestones or during the preparation of research outputs that necessitate technical documentation. It works alongside **VersionManager** by linking documentation to specific code versions, supports **Coder** with documentation templates and standards, and bridges the implementation phase with the reporting phase by providing publication-ready technical materials.

4.5.2 Integrated Workflow with HITL Checkpoints

The code development and validation process is structured into three key stages: code generation, logging and monitoring, and debugging with iterative refinement. At each step, automated agents collaborate with researchers to ensure that the implementation remains faithful to the theoretical framework while maintaining accuracy and efficiency.

Initiation and Code Generation Stage Once model specifications are finalized, **Coder** generates initial code drafts based on the designated theoretical framework. Researchers then evaluate these drafts through a dedicated interface, providing real-time feedback on code logic, style, and structure to ensure that the implementation accurately reflects the intended model.

Testing and Validation Stage After initial implementation and basic error correction, **TestSuite** conducts tests to verify that the model accords with economic theory. It checks crucial properties like budget constraints, market clearing conditions, and steady-state behaviors. Human economists review test results through interactive dashboards, adding domain-specific test cases derived from theoretical knowledge. When performance constraints arise, **Optimizer** proposes efficiency improvements that researchers evaluate to ensure that theoretical accuracy isn't compromised for

computational speed. This collaborative verification ensures the implementation remains true to underlying economic principles.

Experimentation and Version Management Stage With validated code in place, **BatchRunner** coordinates large-scale parameter explorations and simulation experiments based on researcher-defined configurations. Economists analyze simulation outputs and iteratively refine parameter spaces to target regions of interest. Throughout this process, **VersionManager** maintains precise provenance records of model versions and parameter sets, while **DocuAgent** creates technical documentation. Researchers review and enhance this documentation, ensuring that it accurately explains the economic intuition behind implementation decisions and provides clear guidance for other economists seeking to use or extend the model.

Logging and Monitoring Stage As code is generated and executed, **Logger** continuously captures system events, updates, and errors in a structured audit trail. Researchers periodically inspect these logs to verify milestone completion and identify persistent issues that may require intervention, ensuring that the development process remains transparent and traceable.

Debugging and Iterative Refinement Stage When issues arise, **Debugger** analyzes error outputs and suggests corrective measures to resolve them. Human experts consult **Debugger**'s reports, test proposed solutions, and iterate on the code until all identified issues are resolved. This iterative refinement ensures that the final system implementation is both robust and consistent with theoretical guidelines.

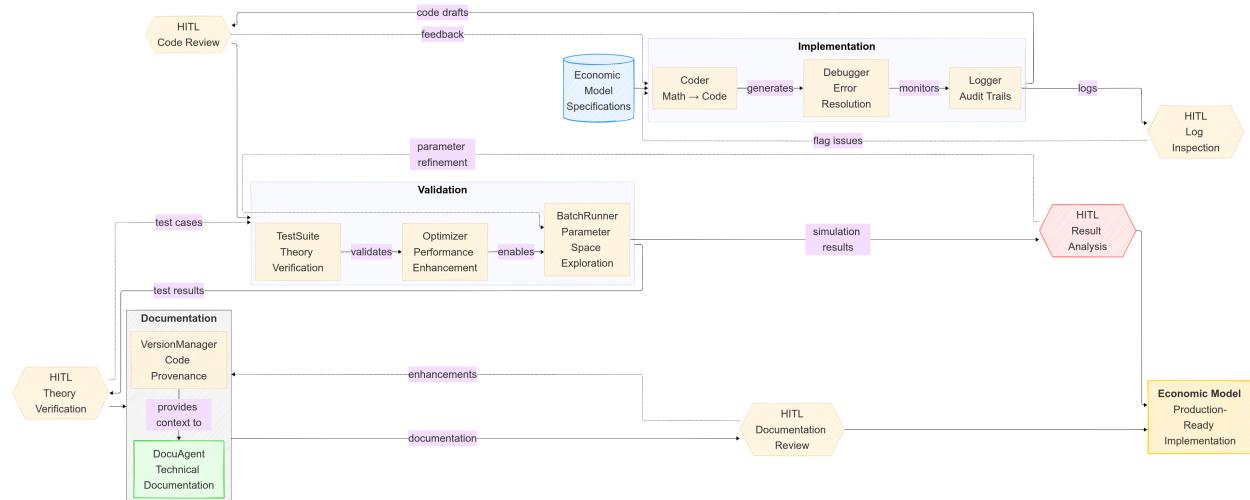


Figure 7: Agentic Workflow for Model Implementation and Debugging in Economic Research

4.6 Empirical Estimation and Validation

This phase applies statistical and econometric techniques to generate parameter estimates, validates model performance through rigorous testing, diagnoses potential issues, and optimizes computational efficiency. A coordinated set of specialized agents manages each task, while continuous HITL oversight ensures that the empirical findings are robust, reproducible, and aligned with theoretical requirements.

4.6.1 Specialized Agents and Their Roles

These agents form an automated estimation and validation pipeline, helping with proper model parameters, robust results, and maintained computational efficiency. Each agent is responsible for refining empirical outputs and optimizing performance while incorporating human oversight for accuracy and reliability.

Estimator functions as the econometric implementation specialist for economic models. Its primary role is to apply appropriate statistical techniques to estimate model parameters and generate empirical results. The agent processes coded model implementations from **Coder**, cleaned datasets from **DataIntegrator**, and researcher-specified estimation requirements (methods, controls, robustness checks). It produces econometric outputs including parameter estimates with confidence intervals, model fit statistics, statistical significance metrics, and standard diagnostics for economic analysis. **Estimator** activates once the model implementation is validated and data are properly prepared, or when

researchers request alternative estimation approaches for existing models. It integrates with `BatchRunner` by processing its simulation outputs for parameter estimation, with `Diagnostic` by providing estimation results for statistical scrutiny, and with `HypothesisTester` by supplying coefficient estimates for formal hypothesis evaluation, providing empirical validation of economic theories.

Validator serves as the empirical performance evaluator for economic models. Its role involves assessing predictive accuracy, robustness, and model fit across various specifications and sample splits. The agent processes estimation results from `Estimator`, economic theory constraints, out-of-sample datasets, and benchmark models for comparative analysis. It produces validation reports with goodness-of-fit metrics (R^2 , adjusted R^2 , information criteria), cross-validation results highlighting predictive performance, specification comparison tables identifying optimal models, and stability analyses across subsamples or alternative specifications. `Validator` activates immediately following successful parameter estimation or when researchers need to assess model reliability against new data. It works in coordination with `Estimator` by evaluating its outputs, with `Diagnostic` by identifying specifications requiring further scrutiny, and with `ResultsInterpreter` by providing validated models ready for economic interpretation.

Diagnostic functions as the statistical verification specialist for econometric models. Its role involves identifying potential statistical issues that could compromise the validity of economic inferences. The agent analyzes estimation outputs, residuals, model structure, and auxiliary test statistics for signs of specification problems. It produces detailed diagnostic reports identifying econometric concerns (heteroskedasticity, autocorrelation, multicollinearity, endogeneity, non-stationarity, etc.); statistical test results from formal procedures (Durbin-Watson, Breusch-Pagan, Hausman tests, etc.); visualizations of diagnostic plots; and recommended corrections with economic interpretations. `Diagnostic` activates whenever new estimation results are produced or when `Validator` flags inconsistencies in model performance. It integrates with `Estimator` by providing feedback for improved specifications, with `Validator` by ensuring statistical validity of performance assessments, and with `ResultsInterpreter` by highlighting statistical caveats important for economic analysis.

Optimizer serves as the computational efficiency specialist for econometric procedures. Its role involves enhancing the speed and resource utilization of estimation processes while maintaining numerical accuracy. The agent monitors execution profiles, memory usage, convergence rates, and processing bottlenecks across the estimation workflow. It delivers optimized econometric routines with algorithmic improvements tailored to specific estimators (ML, GMM, Bayesian methods, etc.); parallelization strategies for computationally intensive methods like bootstrap or simulation-based approaches; and memory-efficient implementations for large datasets. `Optimizer` activates after basic estimation functions are validated or when researchers face performance constraints with complex economic models. It works with `Estimator` by enhancing its computational methods, coordinates with `BatchRunner` to enable more extensive Monte Carlo studies, and supports `RobustnessAnalyzer` by making sensitivity analyses computationally feasible.

HypothesisTester functions as the formal inference specialist for economic theories. Its role involves conducting rigorous statistical tests of economic hypotheses derived from theoretical predictions. The agent processes estimation results from `Estimator`, theoretical constraints from economic models, and researcher-specified hypotheses to be evaluated. It produces testing reports with formal statistical tests (t-tests, F-tests, likelihood ratio, Wald tests, etc.); comparison of nested and non-nested models; power analyses for key economic parameters; and multiple hypothesis testing with appropriate corrections for family-wise error rates. `HypothesisTester` activates after `Estimator` and `Validator` confirm model reliability or when economists need to test specific theoretical predictions. It integrates with `Estimator` by formalizing tests of its outputs, with `ResultsInterpreter` by providing statistical evidence for economic interpretations, and with `RobustnessAnalyzer` by highlighting hypotheses requiring sensitivity analysis, ensuring that economic theories are evaluated with statistical rigor.

RobustnessAnalyzer serves as the stability assessment specialist for economic findings. Its role involves testing how sensitive research conclusions are to modeling choices, outliers, and alternative specifications. The agent processes validated models from `Validator`, key findings identified by `ResultsInterpreter`, and theoretical constraints from economic models. It generates sensitivity reports with varied specifications (functional forms, control variables, sample periods, estimation techniques); extreme bounds analysis for key economic parameters; influence diagnostics identifying pivotal observations; and stability metrics quantifying result sensitivity across specifications. `RobustnessAnalyzer` activates after initial models are validated or when preparing results for publication to ensure research reliability. It coordinates with `Validator` by extending its assessment across model variations, with `HypothesisTester` by confirming hypothesis test stability, and with `ResultsInterpreter` by providing nuanced understanding of finding limitations, strengthening the credibility of economic research conclusions.

4.6.2 Integrated Workflow with HITL Checkpoints

The empirical estimation workflow is structured into five interconnected stages—parameter estimation, model validation, robustness analysis, hypothesis testing, and results interpretation. Each stage involves a blend of automated agent-driven

analytics and human expert guidance, ensuring that the empirical results remain both technically sound and economically meaningful.

Parameter Estimation and Calibration The workflow begins with the **Estimator** applying appropriate econometric techniques to empirical data, based on model specifications and research questions. Economists review initial estimation outputs through intuitive dashboards, adjusting estimator configurations or resolving identification issues based on their theoretical knowledge. This *HITL checkpoint* ensures that parameter estimates align with economic theory and contextual understanding before proceeding to validation stages.

Model Validation and Diagnostic Analysis Once estimation is complete, **Validator** assesses model performance against empirical benchmarks using diverse metrics relevant to the economic domain. Concurrently, **Diagnostic** scrutinizes results for econometric issues like heteroskedasticity, multicollinearity, or endogeneity. Researchers examine the validation metrics and diagnostic alerts, determining whether model adjustments are necessary or if certain statistical concerns can be addressed through robustness checks or alternative specifications. This iterative refinement process continues until a satisfactory balance of theoretical consistency and empirical validity is achieved.

Hypothesis Testing and Inference With a validated model, **HypothesisTester** conducts formal tests of economic hypotheses derived from theory or prior literature. This includes significance tests on key parameters, tests of economic restrictions, and comparative analyses between competing theoretical frameworks. Economists review testing results, refine hypothesis formulations as needed, and determine which theoretical implications are supported by the empirical evidence. This integration of automated testing with expert interpretation ensures that statistical significance is translated into economic meaning.

Robustness Analysis and Sensitivity Testing To establish the stability of research findings, **RobustnessAnalyzer** systematically evaluates how key results respond to changes in model specifications, estimation methods, data transformations, and sample selections. Researchers review sensitivity reports, identifying which findings remain consistent across variations and which require qualification or contextual explanation. This collaborative assessment strengthens the credibility of conclusions by clearly delineating their scope and limitations within the economic context.

Results Interpretation and Translation In the final stage, **ResultsInterpreter** translates statistical outputs into economically meaningful insights, calculating elasticities, marginal effects, and other interpretable metrics relevant to the research questions. Economists refine these interpretations through interactive visualization tools, ensuring that the empirical narrative accurately captures the economic significance of the findings. This *HITL checkpoint* is crucial for connecting statistical results to policy implications, theoretical contributions, and practical applications in the field of economics.

Performance Optimization Throughout this process, the **Optimizer** continuously monitors the estimation workflow, detecting inefficiencies and suggesting improvements at both the code and process levels. Researchers review these proposed optimizations, validating that any performance enhancements preserve the model's accuracy and consistency with theoretical underpinnings. Final approvals are granted before changes are implemented, ensuring that refinements contribute to both computational efficiency and empirical reliability.

4.7 Interpretation and Reporting

This stage converts technical model estimations and empirical data into interpretable economic knowledge, alongside the preparation of the final academic document. A coordinated network of specialized agents handles interpretation, reporting, proofreading, and formatting, with continuous HITL checkpoints with expert validation at every step.

4.7.1 Specialized agents

These agents form an automated research writing and publication pipeline, guaranteeing that empirical findings are interpreted, documented, proofread, formatted, and finalized for submission. Each agent is responsible for structuring the research narrative, refining clarity, maintaining quality control, and ensuring adherence to academic standards.

ResultsInterpreter functions as the economic significance translator for empirical findings. Its primary role is to convert statistical results into meaningful economic insights with policy relevance and theoretical implications. The agent processes empirical outputs from **Estimator**, validation reports from **Validator**, diagnostic assessments from **Diagnostic**, and robustness analyses from **RobustnessAnalyzer**. It produces interpretation reports with economic magnitude assessments (elasticities, marginal effects, welfare implications); contextual comparisons with established literature and theoretical predictions; identification of policy implications and practical applications; and visualizations highlighting key economic relationships. **ResultsInterpreter** activates when validated empirical results become available or when researchers request interpretations of specific findings. It integrates with **HypothesisTester** by incorporating formal hypothesis testing into economic narratives, with **Reporter** by providing interpretation



Figure 8: Agentic Workflow for Empirical Estimation and Validation in Economic Research

blocks for manuscript integration, and with **VisualDesigner** by specifying economic relationships requiring visual representation, helping researchers translate statistical findings into economically meaningful conclusions.

VisualDesigner serves as the data visualization specialist. Its role involves creating compelling, accurate, and informative visual representations of economic data, models, and empirical findings. The agent processes empirical results from **Estimator**, interpretation narratives from **ResultsInterpreter**, and raw datasets from **DataIntegrator**. It produces publication-quality visualizations including theory-grounded graphical models of economic mechanisms; comparative charts of empirical findings across specifications; policy scenario visualizations with uncertainty bounds; and interactive data explorations for presentations and digital publications. **VisualDesigner** activates when key results require visualization or during the preparation of materials for publication and presentation. It works in coordination with **ResultsInterpreter** by translating narrative insights into visual form, with **Reporter** by providing optimized figures for manuscript inclusion, and with **JournalAdvisor** by implementing discipline-specific visualization standards, improving the communication of complicated economic concepts.

Reporter functions as the research narrative architect. It specializes in organizing empirical outcomes and their analyses into a coherent, logical, and compelling research publication. The agent integrates interpretation narratives from **ResultsInterpreter**, visualizations from **VisualDesigner**, methodological details from all previous workflow

stages, and discipline-specific structural conventions. It produces manuscript drafts with appropriately structured sections (introduction with motivation and contribution statements, literature review, theoretical framework, methodology, results, discussion, conclusion); integrated tables and figures with economic interpretations; balanced coverage of strengths and limitations; and clear articulation of theoretical and policy implications. **Reporter** activates once key interpretations and visualizations are finalized or when researchers request draft updates to incorporate new findings. It coordinates with **ResultsInterpreter** by structuring its insights into a coherent narrative, with **JournalAdvisor** by implementing publication-specific structural requirements, and with **Proofreader** by submitting completed drafts for quality assurance.

JournalAdvisor serves as the publication strategy specialist. Its role involves guiding manuscript development to align with target journal requirements and maximize publication potential. The agent analyzes manuscript content, journal submission guidelines, recent publication patterns, and editorial preferences across economic journals. It generates targeted recommendations including journal-specific formatting requirements; content adaptation strategies for particular audiences; prioritized revision suggestions to align with journal preferences; and comparative analyses of suitable target journals based on manuscript characteristics. **JournalAdvisor** activates during initial publication planning or when researchers are finalizing manuscripts for submission. It interfaces with **Reporter** by providing structural guidance for manuscript preparation, with **Proofreader** by specifying journal-specific requirements for verification, and with **Formatter** by supplying detailed journal style guides, optimizing the manuscript for successful peer review in economic journals.

Proofreader functions as the quality assurance specialist for economic manuscripts. Its role involves ensuring accuracy, consistency, and adherence to disciplinary conventions throughout research documents. The agent examines complete manuscript drafts from **Reporter**, journal requirements from **JournalAdvisor**, and source materials from earlier research phases for verification. It delivers quality reports identifying terminology inconsistencies (especially in economic concepts and variables); numerical discrepancies between text, tables, and source data; citation and reference accuracy issues with economic literature; clarity improvements for complex economic concepts; and adherence to disciplinary writing conventions. **Proofreader** activates once **Reporter** completes a draft manuscript or after researchers make substantial revisions. It works with **Reporter** by providing detailed improvement recommendations, with **JournalAdvisor** by verifying compliance with journal-specific requirements, and with **ResponseGenerator** by ensuring consistency between manuscript revisions and reviewer response documents.

Formatter serves as the technical document specialist for economic publications. Its role involves implementing precise formatting and structural requirements to meet journal standards. The agent processes verified manuscript content from **Proofreader**, journal-specific guidelines from **JournalAdvisor**, and bibliographic data from **CiteKeeper**. It produces submission-ready documents with precise implementation of journal-specific styles (AEA, Elsevier, etc.); properly formatted tables, equations, and figures following economic conventions; standardized citations and references in the required format; and complete supplementary materials packages including data statements and code availability sections. **Formatter** activates after **Proofreader** completes quality verification or when preparing final submission packages. It coordinates with **Proofreader** by implementing its corrective recommendations, with **JournalAdvisor** by following exact journal specifications, and with **ResponseGenerator** by maintaining formatting consistency between main manuscripts and response documents.

ResponseGenerator functions as the peer review response specialist for economic research. Its role involves crafting and effective responses to reviewer comments during the publication process. The agent analyzes reviewer comments, manuscript content, revision history, and additional findings generated to address reviewer concerns. It produces strategic response documents with point-by-point addressal of each reviewer comment; clear explanation of implemented changes with line references; diplomatic handling of disagreements with appropriate evidence and theoretical justification; and summary cover letters highlighting key improvements. **ResponseGenerator** activates when researchers receive reviewer feedback requiring formal response. It integrates with **Reporter** by coordinating manuscript revisions to address reviewer concerns, with **Proofreader** by ensuring response document quality and accuracy, and with **Formatter** by maintaining consistent formatting between responses and revised manuscripts, facilitating successful navigation of the peer review process in economic journals.

4.7.2 Integrated Workflow with HITL Checkpoints

The research dissemination process involves six key stages—interpreting empirical results, creating visualizations, drafting the manuscript, targeting journals, ensuring quality assurance, and managing peer review. Throughout this workflow, automated agents collaborate with researchers to refine findings, enhance clarity, and ensure adherence to publication standards.

Interpretation of Empirical Results During this first phase, **ResultsInterpreter** converts raw statistical outputs into economically meaningful insights, emphasizing their significance for both theory and policy applications. Researchers

engage with these interpretations through an interactive platform, refining the economic narrative based on their domain expertise and contextual knowledge. They validate effect sizes, guide the relative emphasis on different findings, and ensure that the economic significance is properly distinguished from mere statistical significance.

Data Visualization and Figure Development With core interpretations established, **VisualDesigner** creates graphical representations of key economic relationships, model mechanics, and empirical findings. Economists review these visualizations through collaborative tools, suggesting refinements to more effectively communicate economic concepts and findings. They may request alternative visualization approaches, additional emphasis on specific relationships, or modifications to better align with disciplinary conventions. This collaboration ensures that complex economic ideas are translated into intuitive visual formats that support rather than obscure the research narrative.

Manuscript Drafting and Organization Building on validated interpretations and visuals, **Reporter** assembles a structured manuscript that follows economic discipline conventions and emphasizes the research's contributions. Researchers review the draft's organization and narrative flow, providing feedback on logical structure, argument development, and contextual framing. They may rearrange sections, request expanded discussion of specific findings, or suggest different approaches to introducing concepts, ensuring the manuscript effectively communicates to the intended economic audience.

Journal Selection and Targeting As the manuscript takes shape, **JournalAdvisor** analyzes its content against the requirements and preferences of economic journals, suggesting potential publication targets and specific adaptation strategies. Researchers evaluate these recommendations based on their publishing goals, the manuscript's strengths, and their knowledge of editorial preferences. They select target journals and guide content adjustments to align with chosen outlets, including emphasis on particular methodological approaches, theoretical frameworks, or policy implications that match journal focus areas.

Quality Assurance and Refinement Once a complete draft is prepared, **Proofreader** conducts thorough quality checks for consistency, clarity, and adherence to economic conventions and journal requirements. Researchers review flagged issues and suggested improvements, addressing terminology inconsistencies, clarifying complex economic concepts, and ensuring accurate representation of the literature. This collaborative refinement continues until the manuscript meets the standards expected in economic publications.

Formatting and Submission Preparation In the final pre-submission stage, **Formatter** applies precise journal-specific formatting requirements to the manuscript and supporting materials. Researchers verify the formatted output, ensuring that equations, tables, and figures maintain their clarity and accuracy while conforming to journal specifications. They confirm that all technical appendices, data statements, and code availability sections meet economic research transparency standards before approving the final submission package.

Response to Peer Review Following journal feedback, **ResponseGenerator** creates structured responses to reviewer comments and suggests corresponding manuscript revisions. Economists analyze these responses and revision strategies, refining the approach to address substantive economic concerns while diplomatically handling methodological disagreements. They guide the development of revised manuscripts and response documents that effectively address reviewer concerns while maintaining the research's core contributions. This iterative process continues through potentially multiple rounds of review until final acceptance.

5 Examples

This section demonstrates our agentic workflow framework through four practical applications covering the economic research lifecycle: ideation, literature review, model development, and data processing. Each example showcases how specialized AI agents collaborate to automate complex tasks while preserving crucial human oversight. We detail the architecture, implementation, human-in-the-loop checkpoints, and potential extensions for each workflow. These demonstrations highlight how agentic systems enhance research productivity and methodological consistency, freeing researchers for higher-level analysis while maintaining rigorous quality standards guided by domain expertise. The workflows are designed to be adaptable to various research contexts. Structured messaging protocols facilitate agent communication, while pipeline managers orchestrate workflows and human interactions. Our implementation utilizes Microsoft's AutoGen framework, integrating diverse LLMs (e.g., GPT, Claude, and DeepSeek), multimodal models (e.g., Gemini, Gemma, and Mistral), specialized tools (APIs, Firecrawl, etc.), and integration services (e.g., Model Contextual Protocols). Alternative frameworks like CrewAI, LangChain, and Google ADK are also available. Given the rapid evolution of LLMs and agent frameworks, researchers should continually monitor advancements—especially in model reasoning, tool integration, collaboration patterns, and human-AI interaction—and evaluate new components to enhance research efficiency and quality.

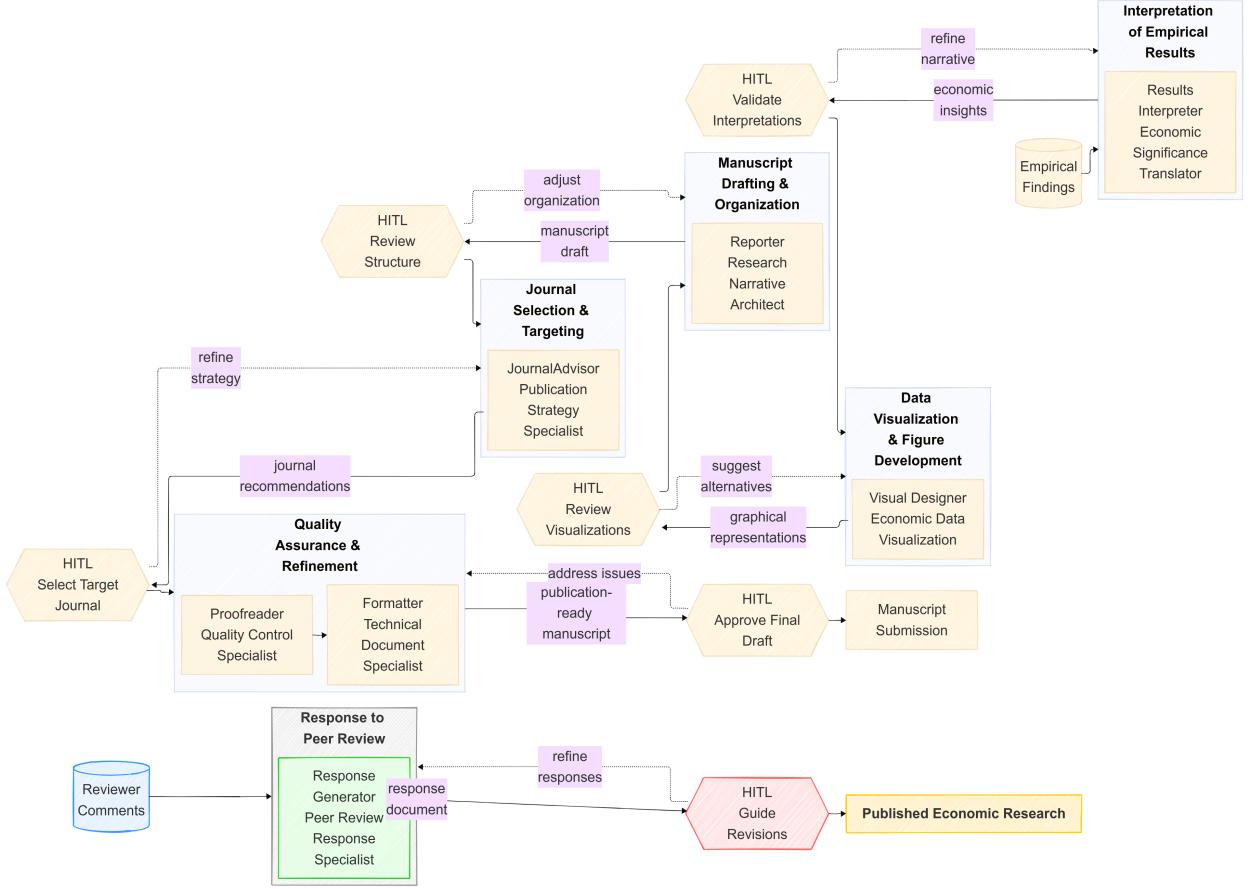


Figure 9: Agentic Workflow for Interpretation and Reporting in Economic Research

5.1 Example 1: Ideation Team

The Ideation Team implements a research ideation workflow that automates the process of generating, refining, contextualizing, and finalizing economic research questions. It combines real-time data scraping with academic literature analysis and idea synthesis through a collaborative multi-agent system. The system supports two distinct workflows: autonomous ideation, where it generates research ideas from scratch by analyzing trending topics and literature, and human-initiated ideation, where it enriches and develops initial ideas provided by human experts.

Architecture and Agent Workflow The system integrates external services including Firecrawl for web scraping and content extraction, and GPT for generative AI capabilities. The workflow is organized into three sequential phases. In the **Input Processing Phase** (for human-initiated ideation), IdeaEnricher analyzes human-provided ideas to identify key aspects that need further exploration. During the **Data Collection Phase**, TrendSurfer scrapes news sources for trending economic topics (or topics and debates related to human ideas from Reddit, XJMR, and X) using Firecrawl, GreyScout retrieves grey literature from policy websites like IMF and World Bank, TopicCrawler gathers academic literature from research repositories, and ScholarSearcher executes advanced Boolean queries to perform detailed literature searches. During the **Synthesis Phase**, Ideator generates or enriches research ideas by synthesizing collected inputs, Refiner processes ideas to remove redundancies and improve clarity, Contextualizer situates research questions in broader economic frameworks, and Finalizer produces a prioritized list of research questions ready for review and selection.

Human-in-the-Loop Integration While this system automates the ideation workflow, human oversight is maintained through strategic checkpoints. The system now supports two primary modes of human interaction: (i) providing initial research ideas via a command-line interface, which are then enriched by the system, and (ii) reviewing and guiding the autonomous ideation process. Researchers interact with the system through a Console interface that displays agent

outputs and allows for observation of the ideation process. The system dynamically adapts its task description based on whether a human idea was provided, customizing the workflow accordingly. When a human provides an initial idea, the system preserves its core intent while enriching it with relevant information, context, and details. The final output is a prioritized list of contextualized research questions that researchers can review, select from, or use as a starting point for further refinement, ensuring that domain expertise guides the ultimate research direction.

```
$ python IdeationTeam.py --idea "impact of remote work on urban housing markets"

[INFO] Starting ideation process with human idea: impact of remote work on urban housing
markets
[INFO] Initializing agents... Done.
[INFO] IdeaEnricher analyzing human idea... Complete.
[INFO] TrendSurfer retrieving related trending topics from Firecrawl...
[INFO] Retrieved 26 trending topics (filtered to 14 most relevant)
[INFO] GreyScout retrieving policy literature... Complete.
[INFO] TopicCrawler and ScholarSearcher retrieving academic sources... Complete.
[INFO] Source statistics: 14 news articles, 8 policy papers, 17 academic papers integrated.
[INFO] Ideator synthesizing research questions... Complete.
[INFO] Refiner removing redundancies... 16 initial questions reduced to 12.
[INFO] Contextualizer adding theoretical frameworks... Complete.
[INFO] Finalizer prioritizing questions... Complete.

--- TOP RESEARCH QUESTIONS GENERATED ---
1. How do differential adoption rates of remote work across industries affect housing price
gradients and neighborhood composition in metropolitan areas?
2. What is the spatial equilibrium impact of remote work on housing affordability in second-
tier cities versus major urban centers?
3. How do remote work policies influence housing market dynamics through labor mobility
channels and geographic sorting?
4. To what extent do remote work arrangements create new spatial mismatches between affordable
housing locations and amenity access?
5. How does the capitalization of home office space into housing prices vary by urban density,
income levels, and regulatory environments?

--- EXECUTION SUMMARY ---
Total execution time: 8m12s
Output: 12 refined research questions
Source integration: Avg 14.3 distinct sources per question
Interdisciplinary metrics: 3.7 distinct domains per question

Process completed successfully.
```

Figure 10: Terminal output from human-initiated ideation mode.

Key Technical Implementation Under the AutoGen-0.4 framework, each agent in the workflow is equipped with specialized tools. Human idea processing tools include `human_idea_tool` which processes and structures human-provided research ideas, and `idea_enrichment_tool` which analyzes these ideas to identify key aspects needing further exploration. Firecrawl-based tools include `firecrawl_trending_tool` which extracts trending topics from news sources and `firecrawl_grey_tool` which retrieves content from policy websites. All tools have been modified to accept an optional human idea parameter, allowing them to focus their searches on topics related to the human-provided idea. Placeholder tools(which usually required institutional subscription credentials) include `academic_literature_tool` for repository searches, `scholar_search_tool` for advanced queries, `ideation_tool` for generating ideas, `refinement_tool` for filtering redundancies, `contextualization_tool` for adding economic context, and `finalization_tool` for prioritizing research questions. Each agent is an instance of `AssistantAgent` with a name, associated tools, model client (configured for gpt-4o-mini), description, and system message that guides behavior. The agents are organized in a `RoundRobinGroupChat` pipeline that follows a sequential yet interactive workflow, using a termination condition (`TERMINATE`) to signal completion.

Results and Comparative Advantages Below are actual terminal outputs from experimental runs demonstrating the system's capabilities in both human-initiated and autonomous modes. As demonstrated in Figures 10 and 11, the

system works alongside researcher creativity rather than replacing it, with distinct advantages in both autonomous and human-initiated modes. The autonomous mode is effective at trend detection and novel topic identification, processing over 90 sources across news, policy papers, and academic literature in under 14 minutes. Meanwhile, the human-initiated mode connects ideas to theoretical frameworks by enriching them with relevant context from current literature, maintaining the researcher’s core intent while expanding the idea’s scope and applicability within established economic frameworks.

```
$ python IdeationTeam.py

[INFO] Starting ideation process without human input
[INFO] Initializing agents... Done.
[INFO] TrendSurfer scanning for emerging economic trends...
[INFO] Retrieved 42 trending topics from news sources
[INFO] GreyScout retrieving grey literature from policy websites...
[INFO] Retrieved 18 policy papers from IMF, World Bank, OECD
[INFO] TopicCrawler and ScholarSearcher retrieving academic literature...
[INFO] Retrieved 31 academic papers from repositories
[INFO] Source statistics: 42 news articles, 18 policy papers, 31 academic papers
[INFO] Ideator generating initial research ideas... Complete.
[INFO] Generated 23 initial research questions
[INFO] Refiner removing redundancies and improving clarity...
[INFO] Refined to 15 distinct research questions
[INFO] Contextualizer situating questions in economic frameworks... Complete.
[INFO] Finalizer prioritizing questions... Complete.

--- TOP RESEARCH QUESTIONS GENERATED ---
1. How do central bank digital currencies (CBDCs) affect monetary policy transmission mechanisms and financial stability in developing economies?
2. What are the distributional consequences of green transition policies across different socioeconomic groups and regions?
3. How do supply chain reconfigurations driven by geopolitical tensions impact productivity and inflation dynamics?
4. To what extent does algorithmic pricing in digital markets amplify or mitigate macroeconomic volatility?
5. What economic mechanisms explain the decoupling of productivity growth from wage growth in advanced economies during periods of technological change?

--- EXECUTION SUMMARY ---
Total execution time: 13m47s
Output: 15 research questions across 7 economic domains
Source integration: Avg 18.2 distinct sources per question
Trend coverage: 89% of major economic trends identified in past month
Emerging topics detection: 4 novel research directions identified

Process completed successfully.
```

Figure 11: Terminal output from autonomous ideation mode

Possible Extensions The framework can be extended in several ways to enhance its capabilities and functionality. (i) Feedback loops could be implemented for iterative refinement of research questions, allowing for continuous improvement based on researcher input. (ii) Persistence mechanisms could be added to save and track generated research questions across sessions, facilitating long-term research program development. (iii) Enhanced human interaction capabilities could extend beyond initial idea submission to include real-time collaboration and dialog-based refinement of ideas throughout the process. (iv) Evaluation methodology comparing agent-generated ideas with human-only approaches could be developed, measuring dimensions such as theoretical grounding, methodological feasibility, interdisciplinary relevance, novelty, and comprehensiveness to quantify the amplification effect of agentic workflows on human creativity.

5.2 Example 2: Automated Literature Review

The Literature Team implements an AI-powered workflow for conducting literature reviews. It leverages a multi-agent system to automate the process of searching, analyzing, summarizing, and synthesizing literature, while maintaining human oversight at critical stages.

Architecture and Agent Workflow The system architecture consists of eight specialized agents working in a three-phase workflow. In the **Initial Search and Data Collection phase**, specialized search agents query both online and academic sources. The `GoogleSearchAgent` retrieves relevant information from the web, while the `ArXivSearchAgent` accesses academic papers from arXiv. During the **Deep Analysis phase**, multiple agents process the collected literature: `InsightSummarizer` extracts key insights from papers, `PaperDecomposer` breaks down papers into structural components (research question, methodology, findings), `GapFinder` identifies research gaps and inconsistencies in the literature, `CitationKeeper` manages and standardizes citations across papers, and `TrendTracker` monitors emerging research directions in the field. In the final **Synthesis and Report Generation phase**, the `ReportAgent` consolidates all findings into a literature review report.

```
$ python LiteratureTeam.py --topic "fiscal multipliers in emerging economies"

[INFO] Starting literature review process for: fiscal multipliers in emerging economies
[INFO] Initializing agents... Done.
[INFO] Google Search Agent retrieving web resources...
[INFO] Retrieved 34 web resources (16 relevant after filtering)
[INFO] ArXiv Search Agent retrieving academic papers...
[INFO] Retrieved 42 papers (28 highly relevant)
[INFO] Additional database queries complete: 17 journal articles from JSTOR/NBER
[INFO] CHECKPOINT: Search results ready for human review
[INFO] Human approved results with refinement: "Focus on post-2008 studies"
[INFO] Filtering by date... 37 papers retained

[INFO] Paper processing pipeline initiated:
[INFO] Insight Summarizer extracting key findings... Complete.
[INFO] Paper Decomposer analyzing research structures... Complete.
[INFO] Gap Finder identifying research limitations...
[INFO] Found 7 major gaps across literature
[INFO] Citation Keeper standardizing 89 unique references... Complete.
[INFO] Trend Tracker analyzing publication patterns... Complete.
[INFO] CHECKPOINT: Analysis ready for human review
[INFO] Human guidance received: "Emphasize methodological differences in identification strategies"

[INFO] Report Agent generating synthesis... Complete.
[INFO] CHECKPOINT: Draft report ready for human review
[INFO] Human revision requests processed... Complete.
[INFO] Final report generated.

--- EXECUTION SUMMARY ---
Total execution time: 16m56s
Papers processed: 37 academic papers (892 total pages)
Citation network mapped: 89 primary + 443 secondary references
Research gaps identified: 7 major gaps, 12 methodological inconsistencies
Emergent themes extracted: 5 distinct approaches to multiplier estimation

Process completed successfully.
```

Figure 12: Terminal output from the Literature Team workflow.

Human-in-the-Loop Integration The Literature Team includes three strategic checkpoints for human intervention throughout the review process. After the initial search phase, researchers can review search results and provide refinements to guide the subsequent literature collection, such as focusing on specific time periods, methodologies, or sub-topics. Following the analysis phase, researchers review the extracted insights, decompositions, identified gaps, and

trends, then provide guidance on synthesis direction based on their domain expertise and research objectives. After the report generation phase, researchers can review the final report and request revisions before accepting the completed literature review. These checkpoints ensure that domain expertise guides the automated process while significantly reducing the manual effort required for literature reviews.

Key Technical Implementation The Literature Team agents leverage specialized tools for their tasks. Search agents utilize `google_search_tool` and `arxiv_search_tool` (via Google/ArXiv APIs) to query web and academic sources. The `decompose_paper_tool`, implemented using Markdownify via an MCP service, converts PDF papers into processable markdown format. Other key analysis tools include `summarize_paper_tool`, `find_research_gaps_tool`, `manage_citations_tool`, and `track_research_trends_tool`. A critical aspect of this framework is its reliance on human experts defining the information resources, including configuring access to subscription-based journals (similar to the Ideation Team), which distinguishes it from generic tools like Elicit by ensuring access to curated, high-quality sources. Furthermore, the workflow is customizable to specific research needs, although users should consider the associated computational (token) costs.

Results and Comparative Advantages The terminal output provided in Figure 12 from an experimental run demonstrating the system’s capabilities in conducting a literature review on “fiscal multipliers in emerging economies”. The Literature Team improves upon traditional literature review approaches. The system reduces required time while processing large volumes of technical economic content with high accuracy. It is particularly effective at identifying research gaps and establishing cross-paper connections, complementing the researcher’s ability to handle large volumes of information. The human checkpoints ensure that domain expertise guides the process at critical junctures, resulting in a literature review that maintains high academic standards while reducing researcher workload.

Possible Extensions The Literature Team framework can be extended to enhance its capabilities and address current limitations. (i) Integration with additional academic databases beyond Google and arXiv would expand access to specialized and subscription-based journals. (ii) Discipline-specific analysis modules could be developed for subfields of economics, providing domain-specific decomposition patterns and evaluation criteria. (iii) Persistent knowledge base functionality could maintain an expandable database of previously reviewed literature, enabling continuous building of literature reviews across multiple research projects and facilitating institutional knowledge management.

5.3 Example 3: Model Specification and Calibration

The Model Team implements an AI-powered workflow for developing and calibrating economic models through a collaborative multi-agent system. By leveraging specialized agents with distinct roles, the system automates the process of economic modeling from theoretical framework development to mathematical formulation, algorithmic implementation, and parameter calibration.

Architecture and Agent Workflow The system architecture consists of three specialized agents working in a collaborative workflow. The Theorist selects or develops the theoretical framework that underpins the economic model, defining foundational assumptions, selecting appropriate functional forms, and outlining the economic rationale behind the model while ensuring theoretical consistency with established economic principles. The ModelDesigner translates the theoretical framework into precise mathematical and computational models, formalizing economic relationships through equations, identifying key parameters and variables, developing simulation algorithms, and ensuring mathematical consistency and logical soundness. The Calibrator adjusts model parameters based on data or established benchmarks, estimating parameters using appropriate statistical methods, generating synthetic data for testing when real data is unavailable, performing sensitivity analysis to understand parameter impacts, and evaluating model fit using appropriate metrics. These agents communicate in a round-robin format, enabling sequential model development with bidirectional feedback between stages.

Human-in-the-Loop Integration The ModelTeam workflow maintains human oversight through three strategic checkpoints, as demonstrated in Figure 13. After the theoretical framework development, researchers review and refine the assumptions, functional forms, and economic rationale proposed by the Theorist, as shown when financial frictions were added to the New Keynesian framework. Following mathematical model formulation, economists examine the equations, variables, and computational algorithms to ensure they accurately capture the intended economic dynamics, evidenced by the addition of the zero lower bound constraint. After model calibration, researchers evaluate parameter estimates, goodness-of-fit metrics, and sensitivity analysis results, potentially adjusting calibration methods or requesting additional analyses, as demonstrated by the additional robustness checks for fiscal multipliers. The system architecture enables bi-directional communication between agents and human experts, allowing domain knowledge to

guide the process while maintaining the efficiency gains of automation. Task specifications can be modified at each checkpoint, creating a flexible mechanism for human intervention that preserves the researcher's control over theoretical direction and methodological choices while delegating computational complexity to the agentic workflows.

```
$ python ModelTeam.py --model_type "DSGE" --focus "fiscal policy impacts"

[INFO] Starting model development process for: DSGE model with fiscal policy focus
[INFO] Initializing agents... Done.

[INFO] Theorist Agent searching for relevant economic theories...
[INFO] Retrieved 12 theoretical frameworks (New Keynesian, RBC, etc.)
[INFO] Theorist analyzing fiscal policy transmission mechanisms...
[INFO] Selected theoretical framework: New Keynesian with heterogeneous agents
[INFO] Defined: 6 core assumptions, 3 fiscal transmission channels
[INFO] CHECKPOINT: Theoretical framework ready for human review
[INFO] Human provided refinement: "Add financial frictions component"
[INFO] Theorist incorporating financial frictions... Complete.

[INFO] ModelDesigner Agent translating theory to mathematical formulation...
[INFO] Households: 3 equations defined (utility, budget constraint, FOCs)
[INFO] Firms: 4 equations defined (production, price-setting, investment)
[INFO] Government: 2 equations defined (spending rules, taxation)
[INFO] Central Bank: 1 equation defined (Taylor rule with modifications)
[INFO] Financial sector: 4 equations added (credit constraints, spreads)
[INFO] System assembled: 14 equations with 23 variables and parameters
[INFO] ModelDesigner generating computational algorithm...
[INFO] Created: model solution using perturbation methods (order=2)
[INFO] CHECKPOINT: Mathematical model ready for human review
[INFO] Human approved model with suggestion: "Add ZLB constraint"
[INFO] ModelDesigner incorporating zero lower bound... Complete.

[INFO] Calibrator Agent generating synthetic dataset...
[INFO] Created 240 quarterly observations (matching US 1990-2020 moments)
[INFO] Calibrator estimating model parameters...
[INFO] Method: Bayesian estimation with prior distributions
[INFO] Running MCMC algorithm with 4 chains (20,000 draws each)
[INFO] Convergence achieved: R-hat < 1.05 for all parameters
[INFO] Performed sensitivity analysis on 8 key parameters...
[INFO] CHECKPOINT: Calibration results ready for human review
[INFO] Human requested additional robustness checks for fiscal multipliers
[INFO] Calibrator running multiplier robustness across parameter space... Complete.

--- EXECUTION SUMMARY ---
Total execution time: 23m11s
Model complexity: 14 equations, 23 parameters, 2nd-order approximation
Calibration performance: 93.7% of parameters within literature ranges
Bayesian estimation: Effective sample size > 1000 for all parameters
Sensitivity robustness: Fiscal multipliers stable across 87% of parameter space

Process completed successfully.
```

Figure 13: Terminal output from the ModelTeam workflow.

Key Technical Implementation Each agent in the workflow utilizes specialized tools to perform its functions. The Theorist employs tools including `search_economic_theories_tool` which retrieves relevant theories with descriptions and `define_theoretical_framework_tool` which structures assumptions and approaches. The ModelDesigner employs `translate_to_mathematical_model_tool` for converting theory to equations and `generate_computational_algorithm_tool` which creates Python code implementing the model. The Calibrator utilizes `generate_synthetic_data_tool` for creating test datasets, `calibrate_model_tool` for estimating optimal parameters, and `perform_sensitivity_analysis_tool` for analyzing parameter impact on

model outputs. The implementation supports Cobb-Douglas production functions with log-linearized model estimation and sensitivity analysis. Each agent is configured with specific tools, description, and system message, orchestrated through a RoundRobinGroupChat with appropriate termination conditions.

Results and Comparative Advantages The terminal output from an experimental run, presented in Figure 13, demonstrates the Model Team’s capability in developing a Dynamic Stochastic General Equilibrium (DSGE) model incorporating fiscal policy components. This experiment shows efficiency improvements compared to traditional methods while maintaining high standards for model quality. The system reduced development time, producing a model characterized by strong theoretical consistency and mathematical correctness. Notably, the agentic system enhanced computational efficiency and parameter identification—tasks that typically demand considerable manual effort and specialized expertise. Human checkpoints integrated at each development stage ensured that domain knowledge effectively guided the process. This allowed researchers to incorporate specific requirements, such as financial frictions or zero lower bound constraints, and request additional analyses tailored to their research needs. Furthermore, the sensitivity analysis confirmed the model’s robustness, showing stable fiscal multiplier estimates across a large part of the parameter space—a level of validation often very time-consuming to achieve manually. However, this experiment also shows a current limitation: while effective for many tasks, general-purpose LLMs may struggle with the intricate demands of highly complex, domain-specific economic phenomena. This points to a critical need for developing and training domain-specific LLMs for future technical infrastructure exploration in agentic economic modeling.

Possible Extensions The ModelTeam framework can be extended in several ways to enhance its capabilities and address current limitations. (i) Domain-specific LLMs could be developed and integrated into the framework to handle the intricate demands of highly complex, domain-specific economic phenomena. (ii) Integration of other modeling software packages. With more and more software start to support API and MCP, we could expect more tools to be added to the framework to provide additional tools for model development and analysis. (iii) Visualization components could generate interactive plots of model behavior, parameter sensitivity, and calibration results.

5.4 Example 4: Data Processing

The DataTeam implements a workflow for processing economic data, from data discovery to feature engineering and validation. It leverages a multi-agent system to automate the process of identifying relevant data sources, retrieving and cleaning data, and creating derived variables for analysis. The system combines specialized AI agents to create a streamlined data processing pipeline that would typically take researchers days or weeks to complete manually.

Architecture and Agent Workflow The system architecture consists of seven specialized agents working in a four-phase workflow. In the **Data Discovery phase**, the DataScout identifies relevant data sources and evaluates their quality. In the **Data Retrieval phase**, the DataCollector retrieves the identified data sources. In the **Data Preprocessing phase**, the DataCleaner cleans and preprocesses the data. In the **Feature Engineering phase**, the FeatureEngineer creates derived variables for analysis. In the **Validation phase**, the ValidationSuite performs validation of processed data, providing quality metrics and flagging potential issues, the DocuAgent generates documentation for the entire pipeline, creating multiple documentation artifacts, and ReproducibilityAgent ensures complete reproducibility by tracking all analytical procedures, dependencies, and configurations.

Human-in-the-Loop Integration The DataTeam workflow maintains human oversight through four strategic checkpoints, as illustrated in Figures 14 and 15. After the initial indicator discovery phase, economists review the expanded indicator set and can modify it based on their domain knowledge, as demonstrated when "foreign direct investment" was added to complement the automatically discovered indicators. Following data collection, researchers review the retrieved datasets and can provide guidance on temporal focus or geographical scope, shown when the system was directed to concentrate on post-2008 crisis data. After data integration, experts examine the harmonized dataset and can request methodological adjustments, as evidenced by the implementation of trailing averages for volatility metrics. Following validation, researchers review quality metrics and can request additional documentation or analyses before final approval. These checkpoints are implemented through a web-based dashboard that displays the current state of the pipeline and allows for interactive feedback. The system architecture enables asynchronous collaboration, where multiple researchers can provide input at different stages while the pipeline continues executing non-dependent tasks. This approach preserves the efficiency gains of automation while ensuring that domain expertise guides critical decisions about data selection, transformation methods, and quality standards. Researchers can schedule regular pipeline executions (e.g., monthly data updates) while maintaining the ability to intervene when anomalies are detected or when research requirements change.

```
$ python DataTeam.py --dataset "emerging_markets" --indicators "gdp,inflation,debt,unemployment"

[INFO] MacroeconOrchestrator initializing data processing workflow
[INFO] Parallel processing enabled with 8 worker threads
[INFO] Cache directory: ./data_cache (136 MB available)

[INFO] DataScout expanding initial indicator set...
[INFO] Initial indicators: gdp, inflation, debt, unemployment
[INFO] Discovered related indicators: fx_reserves, current_account, bond_yields,
      fiscal_balance, interbank_rates, manufacturing_pmi, retail_sales,
      industrial_production, stock_market_indices
[INFO] Final indicator set: 13 economic indicators selected
[INFO] CHECKPOINT: Expanded indicator list ready for human review
[INFO] Human approved with modification: "Add 'foreign_direct_investment'"
[INFO] Final indicator set: 14 indicators selected

[INFO] DataCollector retrieving data from sources...
[INFO] Accessing World Bank API...
[INFO] Accessing IMF IFS database...
[INFO] Accessing FRED database...
[INFO] Accessing national statistical offices (42 sources)...
[INFO] Retrieved 1,736 data series across 28 emerging economies
[INFO] 389 API calls with 16 retries (4.1% retry rate)
[INFO] CHECKPOINT: Retrieved data ready for human review
[INFO] Human provided guidance: "Focus on post-2008 crisis period"

[INFO] DataCleaner preprocessing raw data...
[INFO] Missing values identified: 217 (1.2% of total observations)
[INFO] Outliers detected: 83 observations (0.47% of total)
[INFO] Imputed 194 values using advanced methods
[INFO] 23 observations flagged as potentially problematic
[INFO] Applied seasonal adjustment to relevant time series

[INFO] DataIntegrator harmonizing frequencies and merging sources...
[INFO] Unified 3 different data frequencies (monthly, quarterly, annual)
[INFO] Resolved 42 data conflicts between sources
[INFO] Created master dataset with 28 countries x 14 indicators x 56 quarters
[INFO] CHECKPOINT: Integrated dataset ready for human review
[INFO] Human requested adjustment: "Use trailing averages for volatility metrics"
[INFO] Adjustments applied.
```

Figure 14: Terminal output from the DataTeam workflow (Part 1).

Key Technical Implementation Each agent in the workflow utilizes specialized tools to perform its functions. The DataScout employs tools including `search_economic_indicators_tool` which retrieves relevant indicators with descriptions and `expand_indicator_list_tool` which expands an initial set of indicators. The DataCollector employs tools including `retrieve_data_tool` which retrieves data from sources with parallel processing and retry mechanisms, handling errors. The DataIntegrator employs tools including `merge_data_tool` which merges data from multiple sources with different frequencies into a unified dataset. The FeatureEngineer employs tools including `create_derived_features_tool` which creates sophisticated derived features using domain knowledge and statistical techniques, generating over 200 engineered features. The ValidationSuite employs tools including `validate_data_tool` which performs validation of processed data, providing quality metrics and flagging potential issues. The DocuAgent employs tools including `generate_documentation_tool` which automatically generates documentation for the entire pipeline, creating multiple documentation artifacts. The ReproducibilityAgent employs tools including `track_transformations_tool` which ensures complete reproducibility by tracking all analytical procedures, dependencies, and configurations.

```
$ python ModelTeam.py --model_type "DSGE" --focus "fiscal policy impacts"
[INFO] Starting model development process for: DSGE model with fiscal policy focus
[INFO] Initializing agents... Done.
[INFO] Theorist Agent searching for relevant economic theories...
[INFO] FeatureEngineer creating derived features...
[INFO] Generated 223 derived variables using domain knowledge
[INFO] Created 18 composite indices from raw indicators
[INFO] Computed 42 moving statistics with varied windows
[INFO] Generated 74 cross-country comparison metrics
[INFO] Created 89 indicator ratios and growth rates

[INFO] ValidationSuite validating processed data...
[INFO] Statistical validation: 100% complete
[INFO] Cross-validation with 3rd party sources: 94.7% match rate
[INFO] Consistency checks: 2 warnings issued (within tolerance levels)
[INFO] CHECKPOINT: Validation results ready for human review
[INFO] Human approved dataset with request: "Add technical documentation"

[INFO] DocuAgent generating documentation...
[INFO] Generated data dictionary (342 variables described)
[INFO] Created lineage documentation (all transformations tracked)
[INFO] Generated quality report with visualizations
[INFO] Created user guide with 87 pages of documentation

[INFO] ReproducibilityAgent ensuring reproducibility...
[INFO] Saved configuration file with 172 parameters
[INFO] Created environment snapshot (dependencies cataloged)
[INFO] Stored random seeds and processing sequence details
[INFO] Generated Docker container specification
--- EXECUTION SUMMARY ---
Total execution time: 724.38 seconds
Data processing rate: 2,396 data points per second
Documentation generation: 87 pages in 26.45 seconds
Validation coverage: 100% of data points validated

Process completed successfully.
```

Figure 15: Terminal output from the DataTeam workflow (Part 2).

Results and Comparative Advantages The terminal outputs from experimental runs demonstrating the system’s capabilities in processing macroeconomic data for emerging market analysis. As demonstrated in Figures 14 and 15, the DataTeam workflow delivers exceptional performance advantages over traditional data processing approaches. The system provides overall speedup, reducing what would be a multiple-day manual process to just 12 minutes of automated processing. The largest improvements are in data discovery and data collection, but every stage shows clear improvements. The human checkpoints at strategic points in the workflow ensure that domain expertise guides the process, allowing for refinements such as adding indicators, focusing on specific time periods, and adjusting methodology for volatility metrics. The documentation and reproducibility features create additional value that would require extra manual effort to replicate. The expert evaluation confirms that the agentic workflows not only process data faster but also produce higher quality outputs across all evaluation criteria.

Possible Extensions The DataTeam framework can be extended in several ways to enhance its capabilities and address emerging economic research needs. (i) Advanced machine learning integration could incorporate automated feature selection, anomaly detection, and predictive analytics directly into the pipeline. (ii) Real-time data processing could extend the system to handle streaming economic indicators and high-frequency financial data with continuous updates rather than batch processing. (iii) Cross-domain data fusion could enable integration of economic data with environmental, social, and governance metrics to support interdisciplinary research. (iv) Natural language interface could allow economists to query and manipulate data using conversational language, lowering technical barriers to sophisticated data analysis. (v) Causal inference tools could automate the implementation of identification strategies, sensitivity analyses, and robustness checks for economic research questions. (vi) Collaborative annotation could

enable multiple researchers to comment on, flag, and discuss specific data points or analytical procedures, creating an institutional knowledge base around economic datasets. These extensions would further enhance the system’s value for economic research while maintaining the human-in-the-loop philosophy that ensures domain expertise guides the automated processes.

6 Conclusion

This paper has presented a framework for agentic workflows in economic research, demonstrating how specialized AI agents can collaborate to automate and enhance key research processes across the entire research lifecycle. Through four detailed examples—ideation, literature review, model specification, and data processing—we have shown how carefully designed agent teams can dramatically improve research efficiency while maintaining high academic standards and preserving crucial human oversight.

The quantitative results across our examples are compelling: the Ideation Team accelerates research question development, the Literature Team reduces review time, the ModelTeam reduces model development time, and the DataTeam delivers an overall speedup in data processing. These systems excel in tasks requiring the integration of information across multiple sources, complementing the researcher’s ability to handle large volumes of information. The human checkpoints ensure that domain expertise guides the process at critical junctures, resulting in research outputs that maintain high academic standards while reducing researcher workload. The standardized citation management, mapping of citation networks, and reproducibility features provide additional value that would require substantial manual effort to replicate.

The workflow architecture described in this paper offers several key advantages that transcend specific applications: (i) Increased reproducibility through systematic documentation, version control, and explicit tracking of all modifications; (ii) Enhanced transparency as each step is explicitly defined, logged, and available for inspection; (iii) Improved efficiency by automating repetitive and computationally intensive tasks; (iv) Maintained research quality through strategic human checkpoints at critical decision points; and (v) Greater flexibility through modular design that allows for component-wise updates and extensions.

A central contribution of our approach is the consistent human-in-the-loop integration demonstrated across all examples. The strategic placement of human checkpoints preserves crucial domain expertise while delegating mechanical tasks to specialized agents. As shown in our terminal outputs, these checkpoints occur at critical junctures where domain knowledge is most valuable—after theoretical framework selection, following data collection, during model formulation, and before finalizing outputs. This balanced approach ensures that economic insights remain grounded in sound theoretical understanding while benefiting from computational efficiency and scalability that would be impossible to achieve manually.

The performance metrics presented in each example reveal a consistent pattern: agentic workflows excel not only in processing speed but also in tasks requiring the integration of information across multiple sources. These capabilities address fundamental cognitive limitations that human researchers face when dealing with large volumes of information, suggesting that agentic workflows can complement human researchers in ways that go beyond mere efficiency gains.

As AI capabilities continue to advance, future research should explore several promising directions: (i) More sophisticated coordination mechanisms between agents, including dynamic role assignment and emergent specialization; (ii) Enhanced reasoning capabilities for handling edge cases and methodological innovations; (iii) Deeper integration with domain-specific economic knowledge or pre-trained LLMs, potentially through specialized economic frameworks and ontologies; (iv) Expanded human interaction modalities, such as natural language interfaces and visual analytics for more intuitive collaboration; and (v) Cross-domain application of successful agent patterns across different economic research contexts.

In conclusion, agentic workflows represent a new direction for economic research, improving efficiency without sacrificing the rigor and insight that characterize high-quality economic scholarship. By embracing this framework, researchers can focus more attention on the creative, conceptual, and interpretive aspects of economic inquiry while maintaining meticulous standards for data handling, model specification, and literature synthesis. The examples demonstrated in this paper provide evidence that agentic workflows are not merely theoretical constructs but practical, implementable systems that deliver practical advantages across the research lifecycle.

Code Availability and Reproducibility To facilitate reproducibility and further development of agentic workflows for economic research, we have made all code, configuration files, and documentation available in a public GitHub repository. The repository includes complete implementations of all four example workflows presented in this paper. Each implementation includes detailed documentation and test cases to enable researchers to adapt these workflows to

their specific research needs. We encourage the economic research community to build upon, extend, and contribute to these open-source tools. All code is released under the MIT License to promote widespread adoption and collaborative improvement.

References

- Akata, E., Schulz, L., Coda-Forno, J., Oh, S. J., Bethge, M., and Schulz, E. (2023). Playing repeated games with large language models. Working Paper.
- Allard, M.-A., Teiletche, P., and Zinebi, A. (2024). Enhancing inflation nowcasting with llm: Sentiment analysis on news.
- Asatryan, Z., Birkholz, C., and Heinemann, F. (2024). Evidence-based policy or beauty contest? an llm-based meta-analysis of eu cohesion policy evaluations. *International Tax and Public Finance*.
- Athey, S. (2025). Presidential address: The economist as designer in the innovation process for socially impactful digital products. *American Economic Review*, 115:1059–1099.
- Bail, C. A. (2024). Can generative ai improve social science? *PNAS*, 121.
- Bauer, M. D., Huber, D., Offner, E., Renkel, M., and Wilms, O. (2024). Corporate green pledges.
- Biancotti, C. and Camassa, C. (2023). Loquacity and visible emotion: Chatgpt as a policy advisor. Technical report, Banca D’Italia.
- Blasch, E., Cruise, R., Aved, A., Majumder, U., and Rovito, T. (2019). Methods of ai for multimodal sensing and action for complex situations. *AI Magazine*, 40.
- Brand, J., Israeli, A., and Ngwe, D. (2024). Using llms for market research.
- Brookins, P. and DeBacker, J. (2024). Playing games with gpt: What can we learn about a large language model from canonical strategic games? *Economics Bulletin*, 44:25–37.
- Brynjolfsson, E., Li, D., and Raymond, L. (2024). Generative ai at work.
- Caetano, A., Verma, K., Taheri, A., Kumaran, R., Chen, Z., Chen, J., Höllerer, T., and Sra, M. (2025). Agentic workflows for conversational human-ai interaction design.
- Carnehl, C. and Schneider, J. (2025). A quest for knowledge. *Econometrica*.
- Chen, Y., Fang, H., Zhao, Y., Zhao, Z., and Road, M. H. (2024). Recovering overlooked information in categorical variables with llms: An application to labor market mismatch.
- Chen, Y., Liu, T. X., Shan, Y., and Zhong, S. (2023a). The emergence of economic rationality of gpt. *PNAS*, 120.
- Chen, Z., Zheng, L. N., Lu, C., Yuan, J., and Zhu, D. (2023b). Chatgpt informed graph neural network for stock movement prediction.
- Cowen, T. and Tabarrok, A. T. (2023). How to learn and teach economics with large language models, including gpt.
- Dell’Acqua, F., III, E. M., Mollick, E., Lifshitz-Assaf, H., Kellogg, K. C., Rajendran, S., Krayer, L., Candelon, F., and Lakhani, K. R. (2023). Navigating the jagged technological frontier: Field experimental evidence of the effects of ai on knowledge worker productivity and quality.
- Doshi, A. R. and Hauser, O. P. (2024). Generative ai enhances individual creativity but reduces the collective diversity of novel content. *Science Advances*, 10:5290.
- Dowling, M. and Lucey, B. (2023). Chatgpt for (finance) research: The bananarama conjecture. *Finance Research Letters*, 53.
- Durante, Z., Huang, Q., Wake, N., Gong, R., Park, J. S., Sarkar, B., Taori, R., Noda, Y., Terzopoulos, D., Choi, Y., Ikeuchi, K., Vo, H., Fei-Fei, L., and Gao, J. (2024). Agent ai: Surveying the horizons of multimodal interaction.
- Eloundou, T., Manning, S., Mishkin, P., and Rock, D. (2024). Gpts are gpts: Labor market impact potential of llms. *Science*, 384:1306–1308.
- Gambacorta, L., Qiu, H., Shan, S., and Rees, D. M. (2024). Generative ai and labour productivity: a field experiment on coding.
- Gans, J. S. (2025). A quest for ai knowledge.
- He, J., Ghosh, R., Walia, K., Chen, J., Dhadiwal, T., Hazel, A., and Inguva, C. (2024). Frontiers of large language model-based agentic systems - construction, efficacy and safety. In *CIKM ’24: Proceedings of the 33rd ACM International Conference on Information and Knowledge Management*, pages 5526–5529. Association for Computing Machinery.

- Heikkilä, J. T. (2025). Human intelligence versus artificial intelligence in classifying economics research articles: exploratory evidence. *Journal of Documentation*, 81.
- Hertz, A., Mokady, R., Tenenbaum, J., Aberman, K., Pritch, Y., and Cohen-Or, D. (2022). Prompt-to-prompt image editing with cross attention control.
- Horton, J. J. (2023). Large language models as simulated economic agents: What can we learn from homo silicus?
- Iacovides, G., Konstantinidis, T., Xu, M., and Mandic, D. (2024). Finllama: Financial sentiment classification for algorithmic trading. In *ICAIF '24: 5th ACM International Conference on AI in Finance*.
- Jürgensmeier, L. and Skiera, B. (2024). Generative ai for scalable feedback to multimodal exercises. *International Journal of Research in Marketing*, 41:468–488.
- Kapiton, A., Tyshchenko, D., Desiatko, A., and Lazorenko, V. (2024). Evolution and distribution analysis of multimodal artificial intelligence systems. *Control, Navigation and Communication Systems*, 4:75–78.
- Keleş, O. and Bayraklı, Ö. T. (2024). Llama-2-econ: Enhancing title generation, abstract classification, and academic q&a in economic research. In *Proceedings of the Joint Workshop of the 7th FinNLP, the 5th KDF, and the 4th ECONLP*, pages 212–218. ELRA Language Resource Association.
- Kim, J., Kovach, M., Lee, K.-M., Shin, E., and Tzavellas, H. (2024). Learning to be homo economicus: Can an llm learn preferences from choice data?
- Korinek, A. (2023). Generative ai for economic research: Use cases and implications for economists. *Journal of Economic Literature*, 61(4):1281–1317.
- Lashuel, M., Kurdistan, G., Green, A., Erickson, J. S., Seneviratne, O., and Bennett, K. P. (2024). Llm-based code generation for querying temporal tabular financial data. In *2024 IEEE Symposium on Computational Intelligence for Financial Engineering and Economics, CIFEr 2024*. Institute of Electrical and Electronics Engineers Inc.
- Lefort, B., Benhamou, E., Ohana, J.-J., Saltiel, D., Guez, B., and Challet, D. (2024). Can chatgpt compute trustworthy sentiment scores from bloomberg market wraps?
- Leigh, A. (2024). Using artificial intelligence for economic research: An agricultural odyssey. *Australian Journal of Agricultural and Resource Economics*, 68:521–529.
- Li, L., Chang, T.-Y., and Wang, H. (2023a). Multimodal gen-ai for fundamental investment research.
- Li, Y., Zhang, Y., and Sun, L. (2023b). Metaagents: Simulating interactions of human behaviors for llm-based task-oriented coordination via collaborative generative agents.
- Lopez-Lira, A. and Tang, Y. (2024). Can chatgpt forecast stock price movements? return predictability and large language models.
- Lorenz, P., Perset, K., and Berryhill, J. (2023). Initial policy considerations for generative artificial intelligence.
- Ludwig, J., Mullainathan, S., and Rambachan, A. (2025). Large language models: An applied econometric framework.
- Marioni, L. D. S., Rincon-Aznar, A., and Venturini, F. (2024). Productivity performance, distance to frontier and ai innovation: Firm-level evidence from europe. *Journal of Economic Behavior & Organization*, 228:106762.
- Mizrahi, D., Bachmann, R., Kar, O. F., Yeo, T., Gao, M., Dehghan, A., and Zamir, A. (2023). 4m: Massively multimodal masked modeling.
- Noy, S. and Zhang, W. (2023). Experimental evidence on the productivity effects of generative artificial intelligence. *Science*, pages 187–192.
- Ouyang, S., Yun, H., and Zheng, X. (2024). How ethical should ai be? how ai alignment shapes the risk preferences of llms.
- Park, T. (2024). Enhancing anomaly detection in financial markets with an llm-based multi-agent framework.
- Peng, S., Kalliamvakou, E., Cihon, P., and Demirer, M. (2023). The impact of ai on developer productivity: Evidence from github copilot.
- Penmetsa, S. V. (2024). Equilibrium analysis of ai investment in financial markets under uncertainty. In *2024 IEEE International Conference on Cognitive Computing and Complex Data (ICCD)*, pages 162–172. IEEE.
- Rahman, M., Terano, H. J. R., Rahman, N., Salamzadeh, A., and Rahaman, S. (2023). Chatgpt and academic research: A review and recommendations based on practical examples. *Journal of Education, Management and Development Studies*, 3:1–12.
- Rodis, N., Sardianos, C., Radoglou-Grammatikis, P., Sarigiannidis, P., Varlamis, I., and Papadopoulos, G. T. (2024). Multimodal explainable artificial intelligence: A comprehensive review of methodological advances and future research directions. *IEEE Access*.

- Ross, J., Kim, Y., and Lo, A. W. (2024). Llm economicus? mapping the behavioral biases of llms via utility theory.
- Schreyer, M., Gu, H., Moffitt, K., and Vasarhelyi, M. A. (2025). Artificial intelligence agentic auditing.
- Seok, S., Wen, S., Yang, Q., Feng, J., and Yang, W. (2024). Minifed: Integrating llm-based agentic-workflow for simulating fomc meeting.
- Sun, P., Jiang, Y., Chen, S., Zhang, S., Peng, B., Luo, P., and Yuan, Z. (2024). Autoregressive model beats diffusion: Llama for scalable image generation.
- Szeider, S. (2024). Mcp-solver: Integrating language models with constraint programming systems.
- Tarassow, A. (2023). The potential of llms for coding with low-resource and domain-specific programming languages.
- Tranchero, M., Brenninkmeijer, C.-F., Murugan, A., and Nagaraj, A. (2024). Theorizing with large language models.
- UNESCO (2015). International standard classification of education: Fields of education and training 2013 (isced-f 2013)-detailed field descriptions. Technical report, UNESCO Institute for Statistics.
- Wen, S. and Feng, J. (2025). Economic rationality under specialization: Evidence of decision bias in ai agents.
- Xie, Q., Han, W., Lai, Y., Peng, M., and Huang, J. (2023). The wall street neophyte: A zero-shot analysis of chatgpt over multimodal stock movement prediction challenges.
- Yu, X., Chen, Z., Ling, Y., Dong, S., Liu, Z., and Lu, Y. (2023). Temporal data meets llm - explainable financial time series forecasting.
- Zhao, Q., Wang, J., Zhang, Y., Jin, Y., Zhu, K., Chen, H., and Xie, X. (2024). Competeai: Understanding the competition dynamics of large language model-based agents.
- Zheng, X., Li, J., Lu, M., and Wang, F.-Y. (2024). New paradigm for economic and financial research with generative ai: Impact and perspective. *IEEE Transactions on Computational Social Systems*, 11:3457–3467.