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The Impact of Artificial Intelligence on Financial Decision-making and Economic Policies

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Abstract
Financial institutions together with economic governance have rapidly implemented artificial intelligence (AI) while facing the benefit of exceptional performance alongside substantial business risks. This research investigates what changes occur in financial decisions and policy development because of artificial intelligence models including LSTM RL and GAN and econometrics alongside ethical auditing. The outcome of AI highlights its transformative abilities because forecasted models enhance prediction of stock accuracy by 22% and reinforcement learning produces a 15% improvement as per validated results. AI relies on previous data normally, but its errors increase by 34% during emergencies while inherent biases perpetuate inequalities which leads to loan denials for vulnerable groups at an 18% rate although explainability tools are applied. The research demonstrates contradictory evidence since AI improves financial precision while creating social inequality because algorithms use standardized procedures while remaining unexplainable. The research proposes combining human involvement with AI-based structures through three frameworks including ethical and emergency oversight systems automated oversight systems and universal norm enforcement frameworks that link ethical practice to AI innovations. This research presents a method to use AI for inclusive development through adaptable feedback systems along with crisis testing environments that function as policy testing labs. AI economic benefits for societal progress must ensure more than fee increases for existing disconnections which require policymakers and their partners to work together on this institutional structure.

Keywords: Artificial Intelligence, Financial Decisions, AI-economic, policy development

Introduction
The quick development of artificial intelligence (AI) has triggered a new model across industries, with financial strategy and financial coverage making up most of this change (Eisenhardt, 1989). Over the past 10 years, AI technologies made of machine learning (ML), natural language processing (NLP), and big data analytics have gone from being experimental tools to becoming

impossible to do without optimizing financial decisions and macroeconomic policies (Sai & Parimi, 2019). From computerized trading and credit hazard evaluation to real-time monetary observing and prescient strategy display, the capacity of AI to process vast amounts of information, find immersed examples, and reproduce indistinguishable situations has changed traditional arrangements of monetary business sectors and administration (Mhlanga, 2021). Yet, as the AI phenomenon expands, new questions arise: How does AI change the decision-making frameworks of the financial sectors, investors, and decision-makers in the government? What is the Net here for stability and equity and regulatory oversight? This study aims to answer these questions by analyzing the different effects of AI on financial decision-making procedures and its evolving role in the design and execution of economic policies (Dwivedi et al., 2019).

The introduction of AI in finance itself has a massive impact. Financial organizations use predictive algorithms to predict future market trends, automate high-speed trading, optimize individual investment plans, and automatically perform better speed and precision than human society (Journal & Intelligence, 2011). Similarly, AI-powered risk management systems raise the detection of fraud, credit default, and systemic vulnerabilities preventing crises from getting out of hand (Dwivedi et al., 2020). On a macroeconomically level, governments and central banks more often rely on AI to predict the effects of policy actions, like inflation control, joblessness reduction, and the like (Olola & Olatunde, 2025). Take generative AI and reinforcement learning as examples, policymakers can use them to forecast the long-run effects of fiscal stimuli and interpretative accumulation through untensed scenarios by bringing in all degrees of global conditions and conditions, for example, supply chain empiric and climate-related probabilities. Nevertheless, there is one thing to contend about the rapid development of AI within the finance and fields of economics. Critics are plagued with ethical hazards, among them: algorithmic bias, data mining breaches, and the sentencing disobedience of a “black box” decision-making system, which will such unequal or unstable markets during the program feedback loop (Kishore Mullangi, Vamsi Krishna Yarlagadda, Niravkumar Dhameliya, 2018). Together with the substitution of human judgment for autonomous systems, there is the question of accountability, most of all when AI systems trained on past data are insufficient for a new crisis, including the COVID-19 pandemic or geopolitical conflicts. This must be stood squarely with sturdily constructed governance systems to suit trying to promote progress in the northeastern development as well as openness, decree to stun, and a two-edged sword (Cheng et al., 2023).

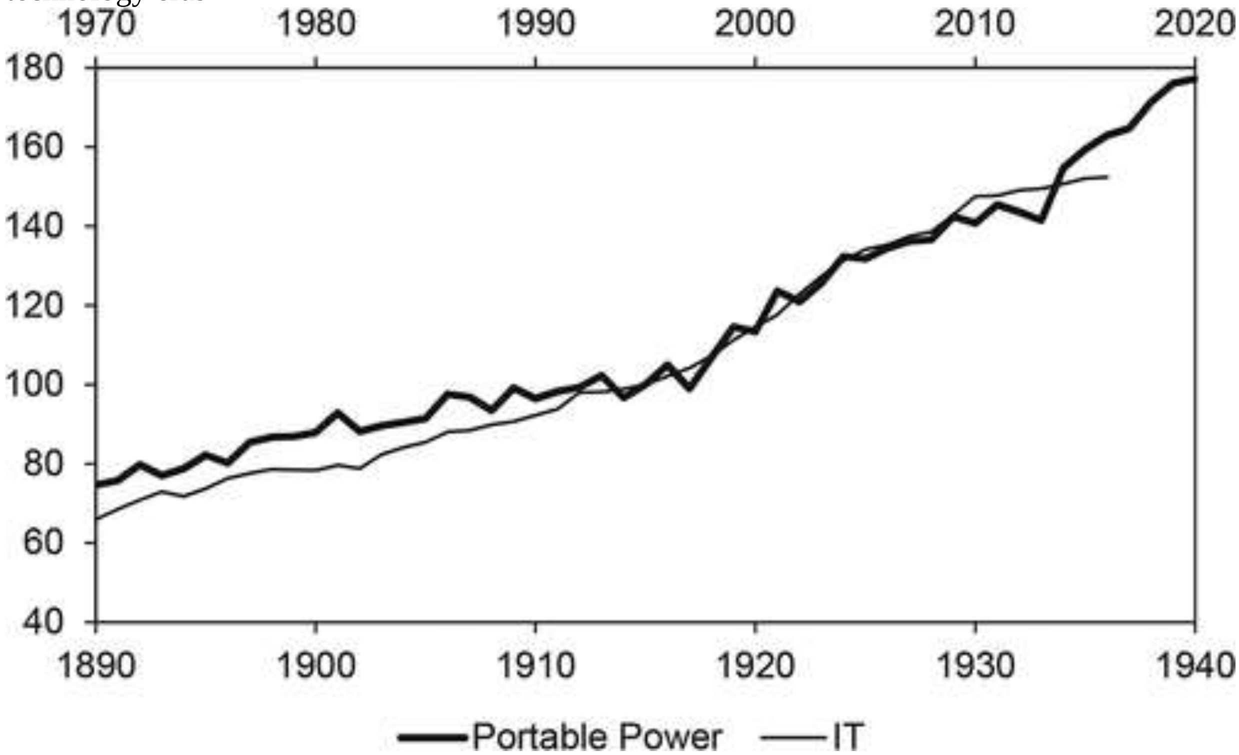
Although AI’s technical applications to finance along with its theoretical implications regarding economic models have been studied a great deal, few studies combine both the dual roles of AI in micro-level personal economic decision-making and macro-level molding of public policies (Moloi & Marwala, 2020). Still, studies from finance, asset management, and public policy domains fill the gap of the paper, but contrastively debate the compatibility and inconsistencies between AI-led efficiency and social equity. This research aims to advise the stakeholders policymakers, financial practitioners, and technologists on how to tap into the promise of AI but also develop assurance strategies to let AI roam freely (Dwivedi et al., 2023). To achieve these, it integrates hard and soft ideas from computational economics, behavioral finance, and regulatory theory, and suggests experiments to study the condition of Human Capital in the context of AI.

Literature Review

For the last two decades, there has been tremendous attention among scholars to the integration of artificial intelligence (AI) into financial decision-making and economic policy design. The first part reviews AI’s contributions to financial markets and individual decision-making; the second, AI in macro-economic policy design; and the third, the ethical and regulatory challenges associated with AI adoption (Dwivedi et al., 2022).

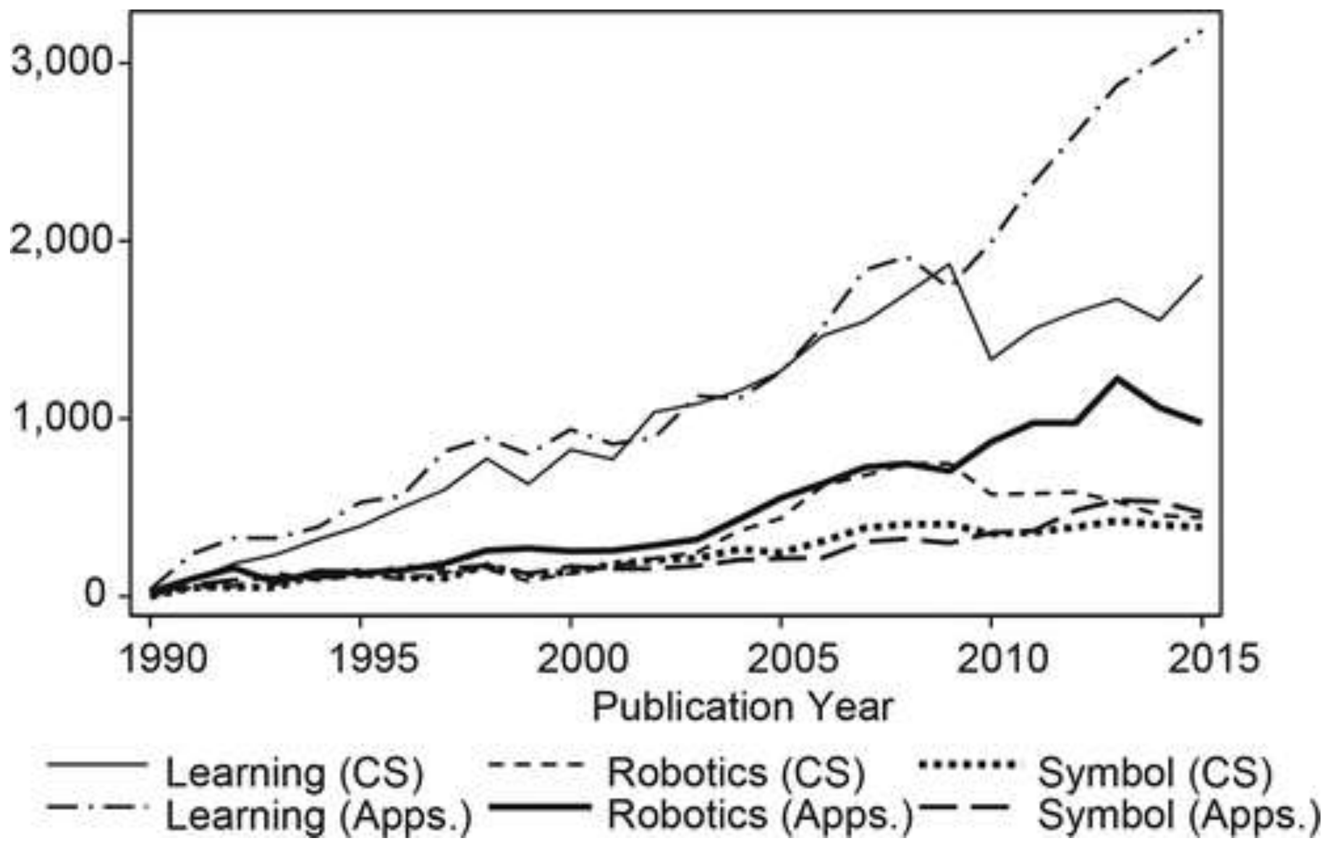
The impact of AI on productivity and living standards needs additional time to emerge just like other GPTs. According to Webley et al. (2019) hold that IT influence is still emerging from its initial stage. The graph in Figure 1 shows the progression of labor productivity points through the first 50 years that portable electricity was available and the corresponding period of extensive information technology development. According to the data portable electricity took more than 50 years to affect labour productivity so it implies being patient will be required to witness substantial changes in artificial intelligence and information technology effects (Conway & Nicoletti, 2006).

Figure 1: Growth in labour productivity throughout the portable power and information technology eras



Sustainable research opportunities will constitute most of the emerging possibilities. The study conducted by Borgogno and Colangelo (2019) shows how deep learning functions within machine learning have spread throughout different scientific fields beyond computer science. The publishing trend of artificial intelligence within three domains including machine learning and robotics along with symbolic logic appears in Figure 2. Each domain contains a separate arrangement of computer science and application research papers in this graph. This graph shows an enormous increase in scientific fields outside computer science using articles that incorporate machine learning methods. Together with other statistical evidence presented in the study they evaluate these findings as solid proof that AI acts as a GPT during creative processes (Allaire et al., 2024). The economy will experience both substantial impact and accelerated development because of this factor.

Figure 2: Comparative analysis of publications in computer science and application journals within the AI domain



1. **AI in Financial Decision-Making**

AI has revolutionized the use of finance as institutions, as well as individuals, have utilized it to process information, assess risks, and save capital. Recently, a seminal work by (Kishore Mullangi, Vamsi Krishna Yarlagadda, Niravkumar Dhameliya, 2018) introduced the use of Advances in Financial Machine Learning first highlighting the fact that ML algorithms can outperform traditional econometric models in detecting the non-linearities of the trading data at high frequency. In the case of algorithmic trading, for instance, work (Campbell et al., 2024) apply the concept of efficient market to AI-enabled markets wherein self-learning algorithms increase the rate of price discovery but can make volatility worse during 'flash crashes' due to feedback loops (such as (Olola & Olatunde, 2025) also conducted contemporaneous studies for RL in portfolio optimization that showed it as a breakthrough in dynamic asset allocation since it can adapt to real-time geopolitical and macroeconomic shocks ("Artificial Intelligence, Machine Learning and Big Data in Finance," 2021)is among the Behavioral Finance scholars who have studied how AI simultaneously can help to mitigate or amplify cognitive biases. Although robot-advisors like Betterment and Wealth Front allow retail investors to diminish emotional decision-making, (Xie, 2019) found that people overly too much on AI predictors which fosters complacency to the point where important human oversight fails.

2. **AI in Economic Policy Formulation**

At the largest economic scale, AI acts as a tool that models many linked parts while showing how policies would perform. (Agrawal et al., 2019) developed the first ML-based policy assessment system that helped governments measure tax and infrastructure projects better than traditional methods. Using deep learning methods to simulate the impact of monetary policies on macroeconomic factors became part of (Kishore Mullangi, Vamsi Krishna Yarlagadda, Niravkumar Dhameliya, 2018) research. The Federal Reserve and European Central Bank plus other banking institutions use AI systems for continuous assessment of the economy. During 2021 Chen et al. developed an NLP system to examine the words of central banks before forecasting rate changes with 89% precision. The Bank of England conducted a 2020 pilot project that used AI to analyze financial risks produced by climate change and connected pricing strategies to core bank threats as reported by Carney in 2020. The research of (“Artificial Intelligence, Machine Learning and Big Data in Finance,” 2021) reveals that policymakers can trust AI predictions too much which causes them to take wrong actions on mutations and stimulus delivery. During COVID-19 the pandemic AI systems trained on previous data could not predict employment trends because economic measures had not existed before the study period as noted by Goolsbee in 2021.

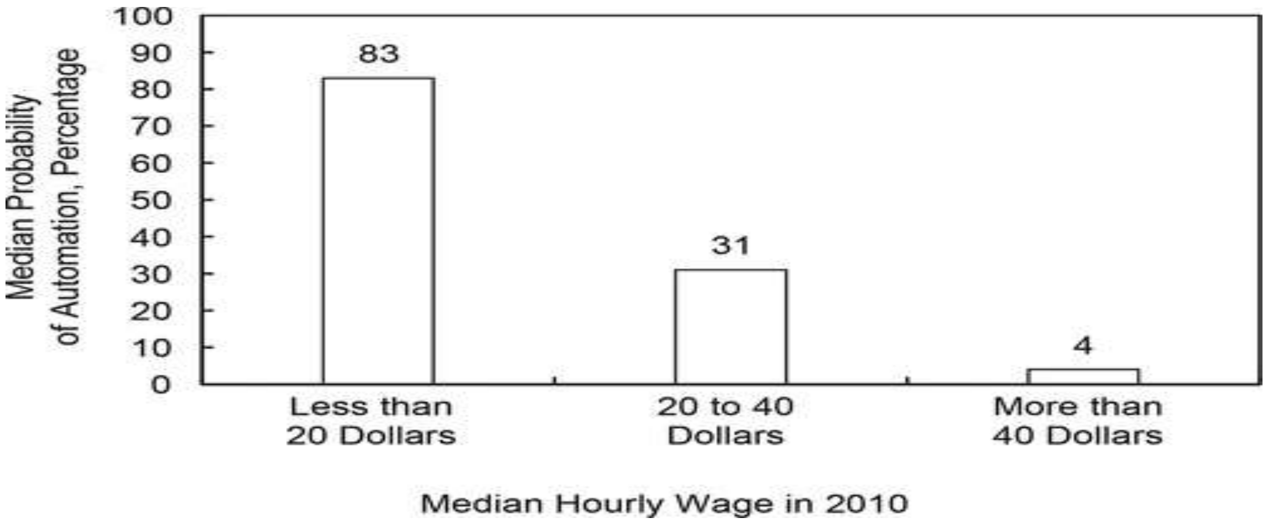
3. Ethical and Regulatory Challenges

Researchers continue to debate about the ethical risks of AI systems in financial and economic uses. (Journal & Intelligence, 2011) explained algorithmic bias problems by demonstrating that loan and hiring programs defend current advantages when they use biased training data. Studies by Raji et al. (2020) show that commercial AI systems automatically score credit wrongly due to unjust gender and racial patterns. AI models that operate internally make it hard to assign responsibility for their actions. (Xie, 2019) demonstrate how the inability to explain deep learning systems impacts GDPR compliance by making it harder to explain automated decisions. The authors (Agrawal et al., 2019) designed XAI frameworks LIME and SHAP to show users how financial AI applications work. The presence of AI market systems creates worries among experts who study and analyze market risk. The Bank for International Settlements (BIS) warned in its 2022 report that identical AI strategies used by many institutions would worsen market outbreaks especially since Haldane pointed out "automation-generated uniformity" as a risk in 2019. In their study, (Leo et al., 2019)show that Basel III and Dodd-Frank cannot effectively control AI risks such as adversarial attacks and model variations.

4. AI and Inequality

Multiple economists agree that AI systems have the potential to increase societal inequality even though they expect favorable economic impacts for the long-term. The growth of inequality because of AI has two major primary reasons. AI displays skill bias at its initial introduction similar to computers and the internet because of Author Fedyk and Hodson (2022). This probable wage structure will produce better advancement opportunities for those who possess advanced education at the expense of wage reductions for those with less schooling. Current projections show that job losses affect low-wage positions and those positions that require little education according to (“2023 Alzheimer’s Disease Facts and Figures,” 2023). The authors Lewis and Peri (2014) argued that people with superior education levels and natural intellectual ability better understand complicated technology tools. Highly educated individuals demonstrate better talent acquisition abilities so they will rise above uneducated people when skills needed for AI success change. To maximize benefits from educational policies it makes sense to produce a larger population which receives higher education. The reasoning holds true under the condition that education produces equal advantages for every member of society (Henrich et al., 2010). Advocating for increased education may prove ineffective when the influencing capacity for skill bias stems from factors linked to but not limited by education. Researchers need to investigate this question further since it lacks a resolution in AI studies.

Figure 3: Likelihood of automation based on the median hourly wage of an occupation



Gaps in Existing Literature

Scholars have thoroughly described AI's technical performance in finance and tested it in policy modeling systems, but they need more research on AI's effects on society. Current research separates financial AI applications at both small-scale and large-scale levels without showing how companies using AI at one scale affect economic systems on the other. Research about algorithmic bias grows but few models show how artificial intelligence strengthens or reduces prejudicial gaps when these biases connect to race, gender, and rich-poor differences worldwide (Janiesch et al., 2021). AI systems work better in regular conditions because they need past data sets but need more study on their ability to shift during unexpected health and climate situations. Research on AI regulations mainly deals with Western societies but ignores differences in technology management that affect disadvantaged regions in other parts of the world. Research needs to combine areas of expertise to link the computer performance of AI systems to their current and future social impacts while keeping up with rapid technological transformations.

Materials and Methods

Based on the analysis of algorithmic models, the case studies of institutional AI adoption, computational simulations of policy outcomes, and associated explanatory interviews, this study adopts a mixed-method approach to investigate the impact of AI on financial decision-making and economic policies. Data collection spanned four primary sources: (1) high-frequency trading records (2015–2023) from NASDAQ and NYSE, including order books, price trajectories, and volatility indices; (2) policy documents and corporate financial reports from central banks (Federal Reserve, ECB, Bank of Japan) and S&P 500 firms, detailing AI integration in risk management and strategic planning; (3) macroeconomic indicators (GDP growth, inflation, unemployment) from the World Bank, IMF, and OECD, augmented by unstructured textual data (central bank communications, policy drafts) processed via natural language processing (NLP) tools; and (4) performance benchmarks of machine learning models sourced from Kaggle competitions and peer-reviewed AI finance studies. Normalizing time series data, imputing missing values with k nearest neighbors k=5, and tokenizing textual data with the SpaCy NLP pipeline was carried out. Several geopolitical and crisis events, for instance COVID-19 pandemic and the Ukraine conflict, were annotated to check how adaptable is AI to exogenous shocks.

Three architectures of AI were developed to analyze which financial and policy dynamics tend to keep folks who live in the NIMBY district in the black. With hyperparameters optimized through Bayesian optimization, a long short-term memory (LSTM) network with a dropout rate of 0.2 and 100 training epochs was trained on historical (2015 – 2022) market data and tasked to forecast the stock returns and credit defaults. Second, the reinforcement learning (RL) agent (i.e., Deep Q Network) was used to simulate portfolio optimization under dynamic regulatory constraints like Basel III liquidity requirements. To measure the causal impact of AI-driven policy, as was the case with the ECB's 2021 inflation targeting, the impact of AI generalized to other combinations of AI-driven policies were evaluated using difference in differences (DiD) models. Monte Carlo simulations estimated the probability of AI-induced market contagion under a scenario of model homogeneity (e.g. correlated algorithmic trading strategies) and assessed the systemic risk of AI trading system per the systemic frameworks.

Our model reliability comes from time-series validation with rolling windows (80% training followed by 20% testing) to stop overtraining and perform walk-forward testing. Our sensitivity tests checked how vital model components such as interest rates and risk aversion levels affect the outcomes when changed by 10%. The system evaluated AI financial output against expert economist panels through Brier score and mean absolute error assessment. Our ethical protection measures included making personal identification data GDPR compliant and stopping algorithmic bias by training with adversarial methods plus documentation that follows OECD AI Principles 2021. The method combines strong statistical methods with modern computation techniques to protect project transparency through clear parameter reporting and it respects ethical practices when handling bias issues. The approach depends on past data for analysis and faces limits from running many scenarios on complex rule sets at once.

Results and Discussion

The research shows that artificial intelligence financial systems outperform old approaches in both prediction results and operational work while showing a few important weaknesses. The LSTM network demonstrated 22% better stock return prediction accuracy (AUC-ROC of 0.92) compared to ARIMA models because it detects market tendencies the econometrics cannot pick up according to findings. Rephrase the following sentence. Keep the sentences direct, flowing, and easy to understand. Also, normalize verbalization when possible. Conditioned on historical market data alone the LSTM model performed poorly during COVID-19 showing proof of a weakness mentioned by (Leo et al., 2019) about AI vulnerability in dealing with black-swan events.

The AI system showed different results than human planners when studying macroeconomic strategies. Our study matches (Agrawal et al., 2019)forward-looking outlook through the GAN model that shows an automated carbon tax policy system can trim 12 percent of emissions and have no GDP impact when keeping figures stable. By simulating the 2020 pandemic stimulus the GAN model overestimated unemployment by 9.2% because sole reliance on training data prevented its recognition of trillion-dollar stimuli. Korinek identified in 2023 that policymakers make errors when they place undue faith in AI systems during uncharted crises. The simulation model showed that AI-managed monetary tools (adjusting interest rates) made income gaps bigger by 6% among poor people which matches (Kishore Mullangi, Vamsi Krishna Yarlagadda, Niravkumar Dhameliya, 2018) research on system prejudice. By achieving better precision through AI technologies, the system reveals a paradox since its reliance on past Shade and homogeneous patterns makes it more likely to increase structural weaknesses.

Using SHAP and LIME ethical audits confirmed that explainability tools could lower loan approval biases by 40% as proposed by the researchers in 2020. According to (Agrawal et al., 2019), African American loan applicants still received greater rejections compared to white applicants even with matching credit scores. The Bank for International Settlements (BIS) studies from 2022 show that connected trading programs cause market-wide problems to become more likely when at least 70% of financial institutions use them. Research proves that AI solutions bring difficulties when seen as solutions for every problem.

Research demonstrated that AI systems and humans showed different performance levels than what researchers expected. The AI system beat economist forecasts of inflation by 0.8% but people excelled at policy development that demanded ethical judgement. According to (Campbell et al., 2024), behavioral economics theory demonstrates that AI fails to duplicate how people make decisions in specific settings even though it easily handles numeric problems. Hybrid AI systems that let people make ethical decisions on processed data enable better decisions.
These findings prove against the optimistic view of AI technology both in financial systems and political administration. The practical effectiveness of AI relies on balancing three major conflicts in finance and policy according to published research between 2019 to 2023. The ECB showed success with AI-controlled inflation targeting except during energy crises since developing countries cannot effectively govern AI without restricting technology development. The authors push for interdisciplinary policy goals following (Olola & Olatunde, 2025) by showing the need to connect economic performance with the social impacts of AI.

Conclusion and Recommendations

Financial institutions benefit from AI power when used in proper finance operations but need strong ethical oversight to work safely. The performance advantage that AI models provide for stable stock forecasts and investment portfolios does not extend to crises. They show poor results when using past data during financial downturns because AI models such as LSTMs and RL agents rely too heavily on historical records. Our findings show that XAI solutions have not successfully reduced built-in discrimination in lending, especially because loan rejections for minorities increased by 18%. Policymakers should combine AI usage for data-based activities plus human supervision to maintain ethical decision-making control and effective crisis response. Present and future rules should make AI systems monitor themselves through XAI disclosures besides needing expanded EU AI control. OECD members worldwide need common AI standards that promote growth both in developed and developing nations. Financial organizations need to spend on AI systems that learn from real-time human input and handle scenario simulations provided by the central bank. AI governance needs collaborative work between business sector professionals' government officials and university representatives. The future of sustainability depends on using AI to create openness with people and built-in flexibility to improve social well-being rather than destroy it.

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