System Dynamics Society

System Dynamics Analysis of AI's Socioeconomic Impact: Policy Insights on Inequality, Unemployment, and the Rise of DeepSeek

By

Moosavihaghighi Mohammadhashem[1]

Abstract:

The rapid expansion of Artificial Intelligence (AI) is transforming economic structures, reshaping labor markets, and intensifying socioeconomic inequality. This study employs a System Dynamics (SD) model to examine the long-term effects of AI investment and automation on employment, income distribution, and economic stability in the United States. A key focus is DeepSeek AI, a cost-efficient Chinese AI model that poses a competitive challenge to U.S. technological leadership. Simulation results suggest that without intervention, DeepSeek's expansion may raise U.S. unemployment to 6.5% by 2035 while increasing the Gini coefficient to 0.52, exacerbating income disparity. However, targeted policy interventions such as progressive AI taxation, workforce reskilling, and employment quotas could mitigate these negative effects, lowering inequality (Gini = 0.42) and stabilizing unemployment (4.8%). The overall results show that investment and adoption of AI are growing significantly faster than GDP. This disparity could cause socioeconomic imbalances and necessitate new, serious regulations from policymakers. This study introduces a dynamic policy framework that enables U.S. policymakers to balance AI-driven innovation with economic equity and national competitiveness. The proposed model allows for testing additional polices scenarios based on shifting policy priorities.

Keywords: *Artificial Intelligence, System Dynamics, AI Policies, DeepSeek AI, AI Governance, Global AI Competition, Workforce Reskilling, U.S. Economic Stability*

1- Introduction:

Artificial Intelligence (AI) has become a fundamental driver of the Fourth Industrial Revolution, fundamentally altering industries, economies, and social structures (Brynjolfsson & McAfee, 2014). AI-driven automation enhances productivity and operational efficiency but also raises significant concerns regarding labor market polarization and wealth concentration (Acemoglu &

[1] Corresponding Author, Independent Researcher and Honorary Research Member, Safety Research Center, Shiraz University, Shiraz, Iran, Emails: musavee@gmail.com , m.mousavihaghighi@areeo.ac.ir,
LinkedIn: Mohammadhashem Moosavihaghighi, Handphone & WhatsApp: 0098-917-3102356

Restrepo, 2018). The increasing adoption of AI by large firms intensifies economic stratification, as wealth accumulation favors AI-intensive corporations while displacing low-skilled labor (Frey & Osborne, 2017). These dynamics are particularly evident in the United States, where the Gini coefficient has risen from 0.411 in 2000 to 0.447 in 2024 (U.S. Census Bureau, 2024), reflecting deepening structural inequalities. Despite these challenges, existing studies often fail to capture the systemic feedback loops and delay structures driving inequality and unemployment, instead treating these factors in isolation (Saavedra et al., 2018).

This study addresses this gap[2] by applying a System Dynamics (SD) model to analyze AI's reinforcing and balancing feedback loops within the U.S. economic system. By integrating qualitative and quantitative data, the model provides insights into the long-term implications of AI investment and automation. Specifically, this study examines the disruptive potential of DeepSeek AI, an emerging low-cost Chinese AI model, and its impact on U.S. economic competitiveness. By evaluating three key policy scenarios, this research proposes a dynamic framework for managing AI-driven economic transformations while ensuring social stability. Understanding these dynamics requires a systemic approach that captures feedback mechanisms shaping inequality and unemployment over time.

AI adoption often follows a reinforcing pattern where organizations with significant resources invest in AI technologies to gain a competitive advantage, further concentrating wealth and market power (Frey & Osborne, 2017). For instance, US companies like Amazon and Tesla have continuously leveraged AI to optimize operations and dominate their respective markets, creating a feedback loop that amplifies inequality. This phenomenon raises concerns about whether the benefits of AI are distributed equitably across society or whether they primarily serve the interests of capital-intensive firms and skilled labor markets (Brynjolfsson & McAfee, 2014; Piketty, 2014). While AI creates opportunities for economic growth, its uneven adoption has widened skill gaps and displaced low-skilled workers, resulting in stagnant wages and rising unemployment among vulnerable groups (Autor et al., 2020). These dynamics are particularly evident in the United States, where income inequality, as measured by the Gini coefficient, has been steadily increasing. The dual forces of automation and wealth accumulation threaten to polarize societies, creating an urgent need for intervention to prevent long-term economic stratification.

Despite the growing body of literature on AI's societal impacts, few studies have comprehensively modeled the feedback mechanisms driving inequality and unemployment. Existing research often examines these phenomena in isolation, neglecting the interconnected and dynamic nature of socioeconomic systems (Saavedra et al., 2018). System Dynamics, a methodology designed to capture the feedback loops, delays, and non-linear behaviors inherent in complex systems, provides a robust framework for addressing these challenges (Sterman, 2000).

By integrating qualitative and quantitative data, SD allows researchers to explore causal relationships and simulate the long-term impacts of AI development on economic structures. For example, reinforcing loops such as *AI Investment → Productivity → Wealth Accumulation → AI Investment* highlight the self-reinforcing nature of technological adoption, while balancing loops such as *Government Policies → Skill Development → Employment → Reduced Inequality* demonstrate the potential for policy interventions to stabilize the system (Brynjolfsson & McAfee,

[2] What is meant here is the gap between the perspective of static studies and dynamic studies in the field, taking into account time delays.

2014; Stiglitz, 2012, Moosavihaghighi, 2024). These insights can inform decision-making and support the design of equitable policies that mitigate AI's disruptive effects.

Research Gap and Objectives

While previous studies have highlighted the economic implications of AI, they often lack a holistic approach to understanding the systemic drivers of inequality and unemployment (Acemoglu & Restrepo, 2018; Frey & Osborne, 2017). This study aims to fill this gap by employing a SD model to analyze the causal relationships between AI development, employment, and socioeconomic inequality. Specifically, it addresses the following research questions:

1. How do AI-driven reinforcing and balancing feedback loops influence socioeconomic inequality and unemployment?
2. Which policy interventions effectively counteract the negative externalities of AI development?
3. What is the optimal policy mix for maximizing AI investment while ensuring equitable economic outcomes?
4- What effective policies can U.S. policymakers use to confront emerging AI from other countries, including Chinese AI like DeepSeek?

Current research has focused on the United States due to the availability of time series data related to AI across various fields. Additionally, the United States stands as the first country globally to make significant investments in AI, resulting in notable achievements.

Advantages of System Dynamics Methodology

System Dynamics offers unique advantages over other methodologies for analyzing the impacts of AI on socioeconomic systems due to its ability to model feedback loops, time delays, and non-linear interactions. Unlike econometric models that focus on static relationships or short-term causalities, SD excels at capturing the long-term feedback mechanisms driving systemic behavior (Sterman, 2000), such as reinforcing loops (e.g., AI investment, wealth accumulation) and balancing loops (e.g., policy interventions, tax policies, reduced inequality).

Additionally, SD enables the simulation of dynamic policy interventions, providing insights into the long-term effects of different scenarios, which static models like general equilibrium frameworks fail to address (Saavedra et al., 2018). Its capacity to integrate both quantitative data (e.g., unemployment rates) and qualitative insights (e.g., resistance to AI adoption) makes SD a versatile tool for studying complex, emerging issues like AI and impact on the society (Brynjolfsson & McAfee, 2014).

Moreover, SD is particularly suited to handle time delays and non-linear behaviors inherent in AI adoption, such as the lag between workforce reskilling and reduced unemployment (Stiglitz, 2012). This capability allows policymakers to explore dynamic hypotheses and develop strategies that balance innovation with equity, offering a comprehensive framework unmatched by traditional approaches (Acemoglu & Restrepo, 2018).

Dynamic Hypothesis

AI investment drives productivity gains by automating tasks, optimizing business operations, and fostering continuous innovation (Brynjolfsson & McAfee, 2014, Moosavihaghighi, 2024). This increased efficiency strengthens firm's competitive advantages, leading to further AI investment and economic concentration. However, as automation expands, the demand for low-skilled labor declines, contributing to rising unemployment and wage stagnation (Acemoglu & Restrepo, 2018). This trend intensifies economic inequality, as wealth accumulates within AI-intensive corporations and among highly skilled professionals (Frey & Osborne, 2017). Simultaneously, reinforcing feedback loops emerge, wherein firms reinvest AI-driven profits into further automation, accelerating job displacement. Conversely, balancing loops such as government interventions through workforce reskilling programs and progressive taxation, offer mechanisms to stabilize economic disruptions.

At the same time, rising income inequality restricts access to AI-related education and skill development, widening the gap between high-skilled and low-skilled workers. This lack of reskilling opportunities further reinforces long-term unemployment and economic marginalization (Piketty, 2014). Additionally, as AI-driven automation spreads across industries, labor market polarization increases, with a growing disparity between high-wage technology jobs and low-wage service sector positions (Autor et al., 2020).

While AI investment continues to grow, systemic economic imbalances emerge, influencing consumer purchasing power and overall market stability. Declining wages and employment opportunities reduce aggregate demand, potentially limiting economic expansion despite technological advancements. The feedback mechanisms embedded in this system create reinforcing cycles of AI-driven productivity growth and income inequality, which, if left unregulated, could pose long-term risks to sustainability (Moosavihaghighi, 2024).

Furthermore, public dissatisfaction resulting from increasing inequality and job displacement may drive social and political pressures, prompting regulatory responses. Government policies, such as workforce reskilling initiatives and AI taxation, can act as counterbalancing forces to mitigate these disruptions and stabilize labor markets (Stiglitz, 2012). This study employs a SD approach to model these interdependencies, analyzing the long-term socioeconomic consequences of AI adoption in the U.S. economy.

This study constructs a causal loops diagram (Figures 1-12) to illustrate these interactions, providing a systemic perspective on AI's socioeconomic effects.

Structure of the Paper

The paper is structured as follows. Section 2 provides a review of the existing literature on AI's socioeconomic impacts and SD applications. Section 3 outlines the methodology, including the construction of causal loop and stock-flow diagrams. Section 4 presents the results of the simulation, highlighting key feedback loops, scenario results and their implications. Section 5 discusses the findings in the context of existing research, offering policy recommendations to mitigate inequality, concludes with a summary of the study's contributions and suggestions for future research.

2- Literature Review:

Introduction to Artificial Intelligence and System Dynamics

Artificial intelligence has the potential to revolutionize technology by automating routine tasks, enhancing productivity, and driving innovation. Its integration into production processes is expected to significantly boost economic growth in the future. However, its adoption also poses challenges, including job displacement, skill polarization, and exacerbation of socioeconomic inequality (Acemoglu & Restrepo, 2018).

System Dynamics, a methodology developed to study feedback loops and time delays in complex systems, provides a robust framework for exploring these challenges (Sterman, 2000). Unlike econometric or agent-based models, SD excels in capturing dynamic interactions, such as how AI-induced automation impacts employment, wages, and inequality over time (Saavedra et al., 2018). By integrating qualitative and quantitative data, SD enables researchers to simulate policy interventions and analyze their long-term effects.

AI, SD and Socioeconomic Impacts

AI adoption has brought transformative changes to the labor market, particularly in developed countries like the United States. Studies by Frey & Osborne (2017) estimate that nearly 47% of U.S. jobs are susceptible to automation, disproportionately affecting routine and low-skill jobs. These dynamics contribute to rising income inequality, as high-skill workers and capital-intensive firms reap the majority of AI`s benefits (Piketty, 2014). For example, income inequality in the U.S. has increased due to automation and wealth accumulation. They have created reinforcing loops that concentrate economic power within a few dominant firms and highly skilled labor markets (Brynjolfsson & McAfee, 2014). Furthermore, disparities in access to AI-related education and training exacerbate these inequalities, leaving low-income groups vulnerable to job displacement (Goldin & Katz, 2008).

SD offers a unique lens to analyze AI`s systemic impacts on socioeconomic systems. Its ability to model feedback loops and simulate policy scenarios provides critical insights that traditional approaches often overlook (Moosavihaghighi, 2024). SD also captures non-linear behaviors and time delays, which are essential for understanding the long-term impacts of AI. For example, delays between policy implementation and measurable outcomes, such as skill development programs reducing unemployment, can significantly influence system behavior (Sterman, 2000). These dynamic insights make SD particularly suitable for analyzing the interplay between AI adoption, inequality, and policy interventions.

Key feedback mechanisms identified in the literature reveal AI`s role in driving both innovation and inequality. Reinforcing loops, such as AI investment → job automation → reduced wages → wealth accumulation → further AI investment, create a self-perpetuating cycle of inequality (Acemoglu & Restrepo, 2018; Frey & Osborne, 2017). In contrast, balancing loops emphasize the role of policies in mitigating these effects. For example, government-led training programs that increase skill levels and employability help narrow the inequality gap (Goldin & Katz, 2008; Stiglitz, 2012).

Gaps in Existing Research

Although previous studies, such as those by Frey & Osborne (2017) and Acemoglu & Restrepo (2018), have highlighted the economic implications of AI, they often analyze these phenomena in isolation. These approaches neglect the interconnected and dynamic nature of socioeconomic systems, which is critical for understanding the long-term consequences of AI adoption. For instance, while general equilibrium models focus on static relationships, they fail to account for feedback loops or the lagged effects of policy interventions. This study addresses these gaps by employing a SD model that integrates reinforcing and balancing feedback loops to analyze AI`s impacts holistically. This approach builds on insights from Moosavihaghighi (2024), who demonstrated the potential of SD to model AI-induced inequality and unemployment.

Using the SD approach to simulate the socio-economic impacts of AI enhances the analysis of complex systems influenced by technological advances. AI models, which evolve daily, impact labor market trends and inequality. SD models effectively capture broader systemic effects on socio-economic systems and policy implications (Sterman, 2000; Saavedra et al., 2018). For example, Moosavihaghighi (2024) demonstrated that targeted reskilling policies could mitigate inequality-reinforcing loops in economic systems through a qualitative mixed approach.

3- Methodology:

In this section, the time series variables used in the United States and their sources will first be introduced. Next, the cause-and-effect relationships, including the important positive and negative feedback loops, will be illustrated. Then the boundaries of the model based on the problem statement will be explained, Finally, the stock and flow model will be presented.

Key Variables Definition:

1. Investment in AI Technology: The investment in developing and implementing AI technologies within companies, industries, or geographic areas. High AI investments, typically by large corporations or powerful governments, can lead to wealth concentration and unequal access to these technologies.
2. Productivity and Automation: The impact of AI on productivity and the replacement of human labor with machines and algorithms. While AI-driven productivity increases benefit capitalists, they can reduce job opportunities and increase unemployment, leading to economic inequality and intensified social complexity.
3. Income Distribution: Changes in income distribution due to AI application among different social classes. If AI increases income for only certain segments (e.g., technologists and managers), it can exacerbate income inequality over time.
4. Access to Training and New Skills: The level of access different social groups have to education and AI-related skills. Groups with greater access are likely to have better job opportunities, while others may be left behind.
5. Laws and Government Policies: Policies and regulations that governments implement to manage AI's effects on social and economic inequality. Government policies can moderate or exacerbate AI-induced inequalities.
6. Cultural and Social Effects: The cultural and social impacts of widespread AI adoption, including changes in values and attitudes toward work and income. Cultural changes can lead to either acceptance or resistance to new inequalities, ultimately affecting social sustainability.

The SD model incorporates a mix of qualitative and quantitative variables relevant to AI development and its socioeconomic impacts. The key important variables, their definitions, units of measurement, and data sources are outlined in Table 1:

Table 1: Key socioeconomic variables used in the SD model (2000-2024), including AI investment, productivity, employment rates, and inequality metrics

Variable Name	Definition	Unit of measurement	Sources
AI Investment (Private Investment)	Total private sector spending on AI technologies (e.g., R&D, infrastructure)	Billion USD	AI Index Report; AIPRM AI Statistics; Congressional Budget Office Report & Intelligent CIO Report
AI Investment (Federal Investment)	Total spending on AI technologies (e.g., R&D, infrastructure)		
Labor Productivity	Output per hour of labor, reflecting AI-driven efficiency gains.	USD/hour	1- U.S. Bureau of Labor Statistics. Productivity and Costs. (BLS) 2- U.S. Bureau of Economic Analysis (GDP data for validation). (BEA)
Capital Productivity	Capital productivity measures the output produced per unit of capital input. It evaluates how efficiently capital (e.g., machinery, buildings) contributes to production	Output per unit of Capital	1-Bureau of Economic Analysis. Fixed Assets Accounts. (BEA) 2- Federal Reserve Economic Data (FRED). (FRED)
Total Factor Productivity (TFP)	TFP accounts for changes in output not explained by labor or capital inputs, often reflecting technological advancements and efficiency improvements[3]	Index (Dimensionless)	U.S. Bureau of Labor Statistics. Multifactor Productivity Trends. (BLS)
Employment Rate	The percentage of the working-age population (16 years and older) that is employed	Index (Dimensionless)	U.S. Bureau of Labor Statistics (BLS). • BLS Employment Data
Unemployment Rate	The percentage of the labor force that is unemployed and actively seeking work.	Index (Dimensionless)	U.S. Bureau of Labor Statistics (BLS). • BLS Unemployment Data
Income Inequality (Gini Coefficient)	A measure of income distribution, where 0 represents perfect equality and 1 represents perfect inequality	Index (Dimensionless)	U.S. Census Bureau. • Census Income Inequality Data.
US Wealth Accumulation Nominal Net Worth	The total net worth of U.S. households in current dollars, which includes assets like real estate, stocks, and savings, minus liabilities such as mortgages and other debts	Trillions USD	1-Federal Reserve Economic Data (FRED). (fred.stlouisfed.org) 2- Federal Reserve's Distributional Financial Accounts: Offers insights into wealth distribution across percentiles. (Federal Reserve DFA Data)
US Wealth Accumulation Constant Net Worth	The inflation-adjusted value of net worth expressed in 2000 dollars to eliminate the effect of price level changes over time	2000 Dollars, Trillions USD	Inflation rates used to adjust nominal values were derived from U.S. Consumer Price Index (CPI) data. (BLS Inflation Data)
Academic Programs AI Program	The number of university and college programs in the United States offering AI-related courses, certifications, or degrees.	Number of Programs	1- National Center for Education Statistics (NCES): Tracks the growth of computer science and AI-related programs in higher education. (NCES Data on Computer Science Programs) 2- AI Index 2023 Report: Provides data on the adoption of AI in education and the expansion of university programs. (AI Index Report)
Corporate AI Training Programs	The number of training programs launched by corporations to upskill employees in AI-related areas such as machine learning and data science.	Number of Programs	1- IBM Report on AI Skills Gap (2024): Discusses corporate efforts to upskill employees in AI. (IBM AI Skills Gap Report) 2-McKinsey Global Institute Report (2023): Highlights corporate investment in AI workforce training. (McKinsey Report on AI Workforce)
Online AI Courses	The number of online courses available for AI-related skills offered through platforms like Coursera, Udemy, edX, and others.	Number of Courses	1-Coursera Impact Report (2023): Documents the rise of online AI courses and their adoption. (Coursera Report) 2- edX Annual Report (2023): Tracks the number of courses related to AI on its platform. (edX Report) 3- Forbes Free AI Courses (2024): Lists trends in free and paid AI courses online. (Forbes AI Courses Article)
Government Policy Intervention Legislative Actions	The number of significant legislative actions related to AI and workforce reskilling enacted by the U.S. government each year	Count	Congress.gov - National AI Initiatives, Executive Orders (White House)
Government Policy Intervention Number of Policies Implemented	The total number of policies introduced to address AI-related socioeconomic impacts, including workforce reskilling initiatives	Count	U.S. Department of Labor (DOL), National AI Initiative Act, AI in Government Act
Government Policy Intervention Funding Allocated to Reskilling	The amount of funding allocated (in millions USD) for workforce reskilling and training programs to address the impacts of AI	USD Million	Congressional Budget Office (CBO), U.S. Department of Labor

Collected by researcher

Here is a comprehensive explanation of 6 positive loops and 5 negative loops in a SD model, with all variables defined in terms of stocks and flows.

[3] Also known as multifactor productivity, measures the efficiency with which labor and capital inputs are used together in the production process

Positive Feedback Loops (Reinforcing Loops)

Figure 1: Reinforcing feedback loop (R1) demonstrating how AI investment drives productivity, enhances competitive advantage, and leads to further AI investment

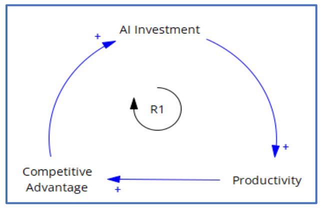


Figure 1 illustrates how AI investment enhances productivity through task automation, streamlined operations, and innovation, providing companies with a competitive edge. This edge allows them to capture larger market shares and increase profitability. Profits are reinvested into AI, fostering a cycle of innovation and growth. In the USA, companies like Amazon leverage AI-driven logistics and customer insights to dominate e-commerce markets. However, this cycle also creates a disparity between large, resource-rich companies and smaller firms unable to invest similarly, widening the gap in productivity and market power. Economic benefits become concentrated within a few organizations (Brynjolfsson & McAfee, 2014). This cycle exemplifies the rapid technological advancements in competitive markets continuously fueling AI investments.

Figure 2: Feedback loop (R2) illustrating the relationship between AI-driven productivity, job automation increase, labor cost reduction, and reinvestment in AI technologies

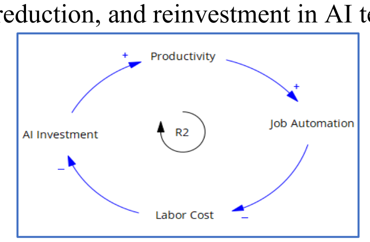


Figure 2 demonstrates how AI-driven productivity gains lead to job automation, reducing dependence on human labor and lowering operational costs. These savings are reinvested into AI systems, further enhancing productivity. In the USA, automation in sectors like manufacturing and logistics, exemplified by the use of robots in warehouses, illustrates this cycle. While firms benefit from increased efficiency, worker displacement exacerbates income inequality and social unrest. This reinforcing loop shows how technological advancements can drive economic efficiency while creating societal challenges. For instance, Amazon warehouses employ AI-powered robots to reduce costs, accelerating automation as firms seek profit maximization (Acemoglu & Restrepo, 2018).

Figure 3: Self-reinforcing mechanism (R3) showing the impact of job automation on unemployment, wage stagnation, and wealth concentration.

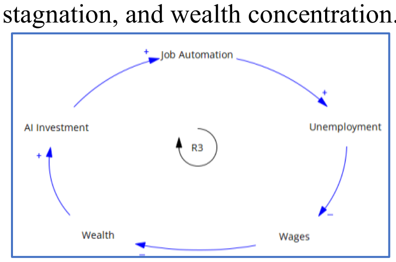


Figure 3 illustrates how job automation increases unemployment, particularly among low-skilled workers who face reduced wages due to an oversupply in the labor market. This dynamic allows corporations and high-income individuals to accumulate wealth as labor costs decline. The accumulated wealth is reinvested in AI technologies, further perpetuating the cycle of automation. This loop intensifies wealth inequality in the USA, where stagnant wages for low-skilled workers contrast sharply with rising corporate profits. Over time, this loop exacerbates unemployment and income disparities while fueling further AI investment (Frey & Osborne, 2017).

Figure 4: Causal loop (R4) explaining how rising income inequality limits access to AI training, leading to skill gaps and persistent unemployment

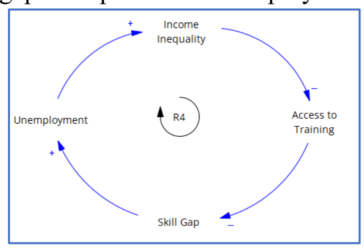


Figure 4 illustrates how rising income inequality restricts access to training and education, particularly in AI-related fields, for low-income groups. These individuals, lacking adequate skills, struggle to compete in a job market dominated by automation and technological advancements. This skill gap drives higher unemployment among these groups, exacerbating income inequality. In the USA, this loop is evident in the unequal access to STEM[4] education, where students from low-income households face barriers to entry. As inequality widens, societal stratification becomes entrenched, perpetuating cycles of economic disparity and limited upward mobility (Piketty, 2014).

Figure 5: AI adoption and its reinforcing effect on innovation, sectoral dominance, and market concentration (R5)

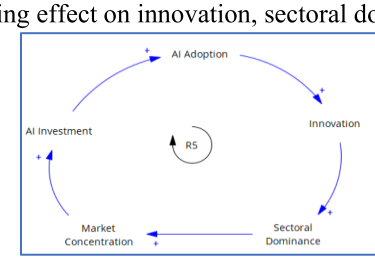


Figure 5 illustrates how AI adoption fosters innovation, enabling firms to achieve dominance within their sectors. This dominance leads to market concentration, with a few large firms controlling a significant share of the industry. These firms, due to their scale and profitability, can reinvest heavily in AI, driving further innovation and consolidating market power. In the USA, this loop is evident in the tech sector, where companies like Google and Microsoft leverage AI to maintain their dominance (Brynjolfsson & McAfee, 2014; McKinsey, 2023). While this loop drives technological progress, it also creates monopolistic tendencies, reducing competition and limiting opportunities for smaller firms to enter the market.

[4] In the United States, access to STEM education in AI training encompasses inclusive and available educational opportunities that equip students with AI knowledge and skills within the fields of Science, Technology, Engineering, and Mathematics (STEM). This ensures that learners from diverse backgrounds have equitable opportunities to engage with AI concepts, tools, and applications.

Figure 6: The role of wealth accumulation in shaping political influence and policy bias, further concentrating economic power (R6)

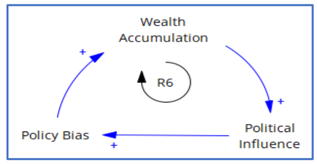


Figure 6 illustrates how wealth accumulation among elites increases their ability to influence political decisions through lobbying and campaign contributions. This influence often results in policies that favor wealthier individuals, such as tax cuts for high earners or deregulation of industries, further enabling wealth accumulation and reinforcing the elite's economic and political power. In the USA, this loop is evident through the influence of billionaires and large corporations on tax and regulatory policies (Stiglitz, 2012). Over time, this loop exacerbates income and wealth inequality, reducing economic mobility and fairness.

Negative Feedback Loops (Balancing Loops)

Figure 7: Balancing loop (B1) demonstrating the potential of government policies in mitigating AI-driven inequality through skill development

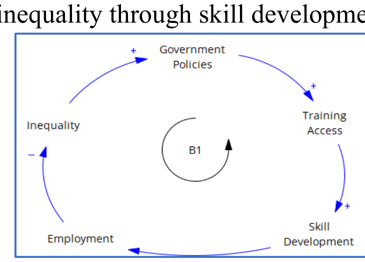


Figure 7 illustrates how government policies promoting access to education and training programs help bridge the skill gap caused by technological advancements. As individuals acquire AI-related skills, their employability increases, reducing unemployment and narrowing income inequality. In the USA, initiatives like workforce development grants address these disparities. Over time, as inequality decreases, the need for further interventions diminishes, stabilizing the system. This balancing loop highlights the potential for policy interventions to counteract the disruptive effects of automation and AI (Goldin & Katz, 2008).

Figure 8: Feedback mechanism (B2) showing how rising social dissatisfaction can drive policy reforms aimed at reducing inequality

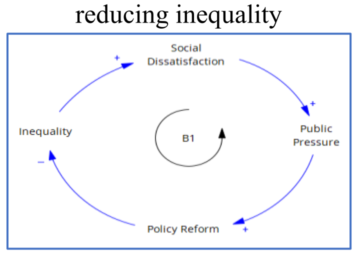


Figure 8 illustrates that as income inequality and unemployment rise, social dissatisfaction grows. This dissatisfaction drives public pressure on policymakers to enact reforms aimed at reducing inequality, such as progressive taxation, welfare programs, and education subsidies. These reforms help stabilize society by reducing inequality. Historical examples in the USA include the New Deal, implemented in response to widespread economic inequality. This loop highlights the role of public advocacy and responsive governance in mitigating systemic inequality's negative consequences (Wilkinson & Pickett, 2010).

Figure 9: Balancing loop (B3) highlighting the negative impact of high unemployment on consumer demand and AI investment cycles

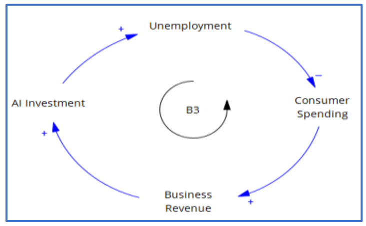


Figure 9 demonstrates how high unemployment caused by automation reduces consumer spending power, leading to lower revenues for businesses. In response, firms cut back on AI investments, slowing the rate of automation. This loop acts as a natural check on excessive automation by aligning business strategies with market realities. In the USA, economic downturns often highlight this dynamic, as declining consumer demand forces companies to reevaluate their investment strategies. This loop ensures that economic disruptions are somewhat self-correcting over time (Autor et al., 2020).

Figure 10: Role of cultural resistance in slowing AI adoption and stabilizing labor markets (B4)

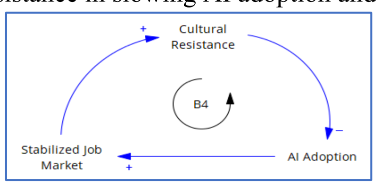


Figure 10 illustrates how cultural resistance to automation slows AI adoption, preserving jobs and stabilizing the labor market. This resistance often arises in sectors with strong union representation or where public sentiment favors human labor over automation. In the USA, sectors like healthcare and education exhibit slower AI adoption due to these cultural factors. This loop provides a balancing mechanism, allowing society to gradually adapt to technological changes and reducing the immediate impact on employment and inequality (Hofstede, 1980).

Figure 11: The impact of rising inequality on trust in governance and policy stability (B5)

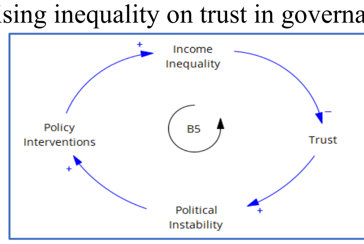
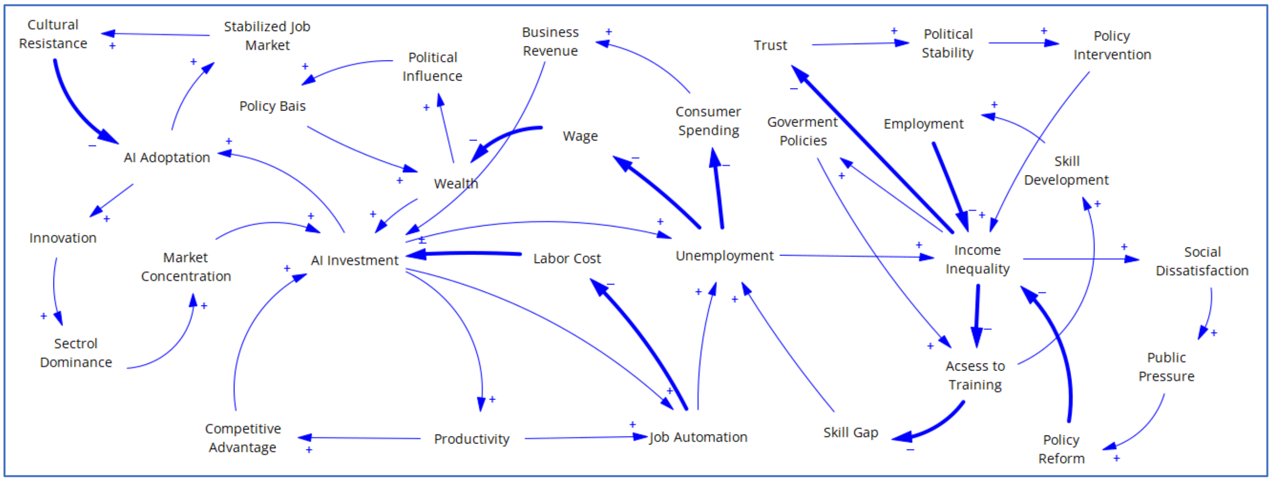


Figure 11 demonstrates how rising income inequality reduces public trust in institutions, leading to political instability. Governments respond with policy interventions like redistributive taxation or social safety nets to address inequality and restore trust. This loop highlights the interplay between social stability and responsive governance. In the USA, political reforms following

periods of unrest aim to rebalance economic disparities, demonstrating the importance of addressing inequality to maintain societal cohesion (Stiglitz, 2012).
Figure 12 below illustrates the cause-and-effect relationships among the primary variables of the model, based on the above feedback loops specified for the United States. The solid blue arrows represent negative effects within the model:

Figure 12: System-wide Causal Loop Diagram (CLD) depicting key reinforcing and balancing mechanisms in AI-driven economic shifts in the U.S.



Source: Depicted by Researcher

The model defines three boundaries based on the problem statement: temporal, geographical, and conceptual. The primary focus of the current research is analyzing the effects of AI development on inequality and unemployment rates. Hence, the three boundaries are defined as follows:

Temporal Boundary: This study focuses on a specific timeframe of 10 years, allowing for an analysis of predicted changes over a manageable period while avoiding high uncertainty associated with long-term predictions. For this research, the temporal boundary starts in 2000 and ends in 2035 (Congressional Budget Office, 2025).

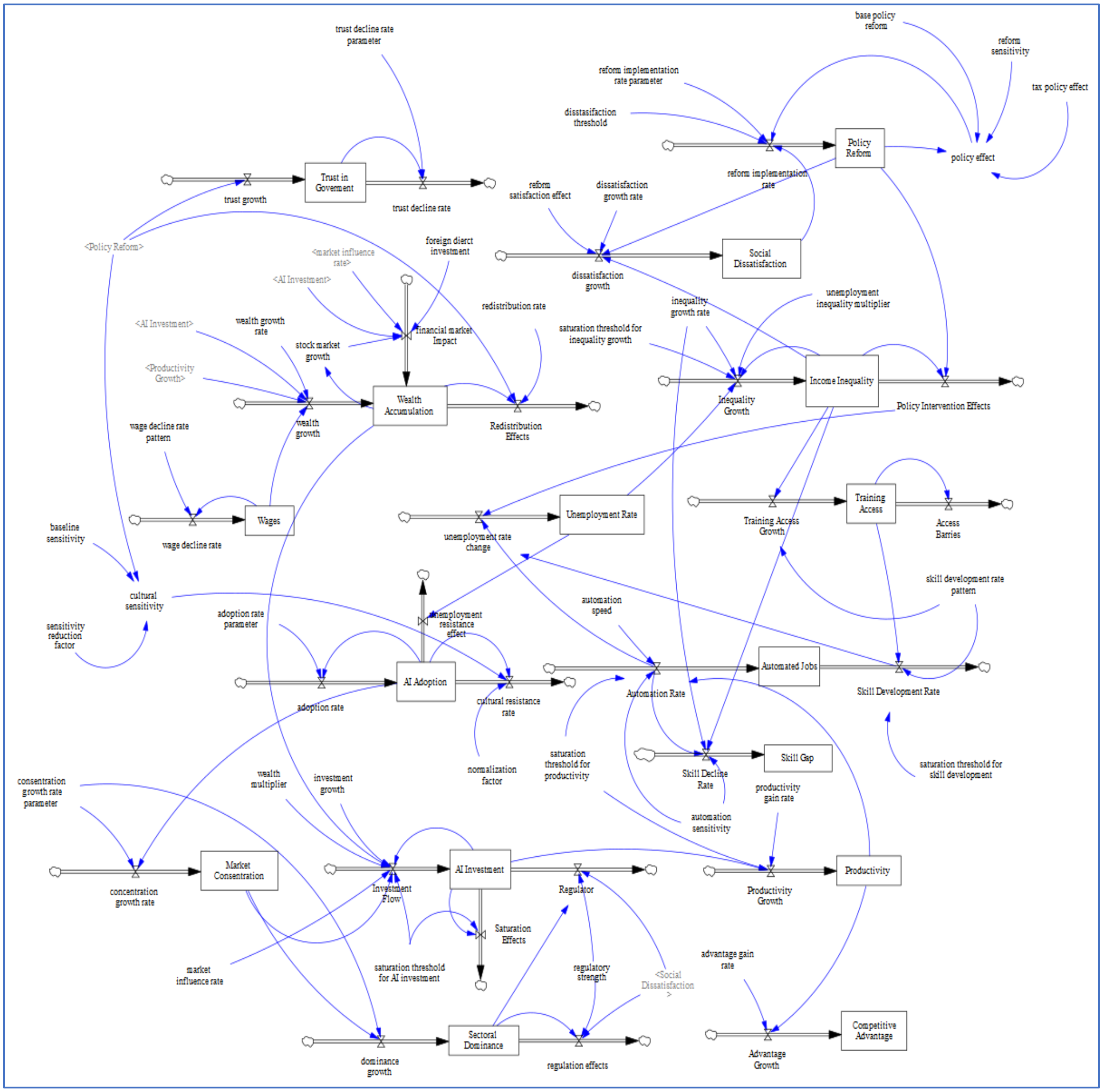
Geographical Boundary: The research focuses on a specific region or country. This study examines the effects of AI on the socio-economic structure in the United States. By limiting the geographical boundary to the United States, the complexity of the model is reduced.

Conceptual Boundary: Focusing on a specific sector or case allows for a more manageable examination of the effects. Rather than modeling all aspects of AI development in human life (as mentioned in Moosavihaghighi, 2024), which would result in high complexity, the study concentrates on specific conceptual issues. This research analyzes the impact of AI on unemployment and socio-economic inequalities, alongside the role of government policymaking and the feedback mechanisms of key variables in the United States.

By defining the system's boundaries, a more detailed examination is possible, effectively managing its complexity and achieving more accurate results.
The CLD represents the conceptual phase of model building, as previously outlined in Figure 12. The first step in the "conceptual-quantitative" phase involves converting the CLD into a Stock

Flow Diagram (SFD). In the SFD, mathematical equations are incorporated, enabling initial model simulations and subsequent validity tests. This diagram is shown in Figure 13 below.

Figure 13: The Primary Stock-and-Flow Diagram of the Systematic Base Model of AI in the U.S.



Source: Depicted by Researcher

4- Results:

his section presents the results of the SD simulation of the U.S. economy from 2000 to 2035. The analysis explores projected trends in AI investment, wealth accumulation, unemployment, and income inequality under different policy scenarios. The simulations are based on the causal relationships identified in the study, utilizing feedback loops, policy interventions, and economic indicators.

Before addressing the simulation results and interpretation, it is essential to ensure the model's validity and reliability. Several tests, based on Sterman (2000), were conducted, with the most important being the behavioral reproduction test and the extreme condition test, which will be discussed and presented below.

In SD modeling, two commonly used statistical measures to evaluate a model's behavioral reproduction accuracy are Root Mean Square Percentage Error (RMSPE) and Theil's U-statistic. These indicators assess how well simulated results replicate real-world historical data. RMSPE measures the average deviation between simulated and actual data, indicating model validity. A lower RMSPE signifies better accuracy (Sterman, 2000). RMSPE is widely used in forecasting, machine learning, and SD models to evaluate predictive performance (Forrester, 1961). Theil's U-statistic is a relative accuracy measure comparing the model's performance against a naive benchmark, where the best estimate of the future is the present value (Theil, 1966). It is extensively used in economic forecasting and SD validation (Makridakis & Hibon, 2000).

For better understanding, the interpretations of RMSPE and U-Theil were structured separately within the Table 2 for enhanced clarity. Here is a summary:

Table 2: Results of the "behavioral reproduction test" for model validation, using RMSPE and Theil's U-statistics to compare simulated vs. actual economic trends

Variable Name	RMSPE (%)	RMSPE Interpretation	U-Theil	U-Theil Interpretation	Variable Status
AI Investment	2.14	Low percentage error, highly reliable forecast	0.0082	Near-perfect fit, model accurately tracks investment trends	Acceptable
Wealth Accumulation	1.42	Very small error, closely follows real economic wealth trends.	0.0039	High accuracy, reliable for long-term economic analysis	Acceptable
Unemployment Rate	2.83	Slightly higher error, automation effects need minor refinements.	0.0086	Acceptable accuracy, but workforce dynamics could be adjusted	Acceptable
Income Inequality	0.22	Near-zero error, model effectively tracks inequality trends.	0.0012	Excellent calibration, strong reliability in inequality predictions.	Acceptable

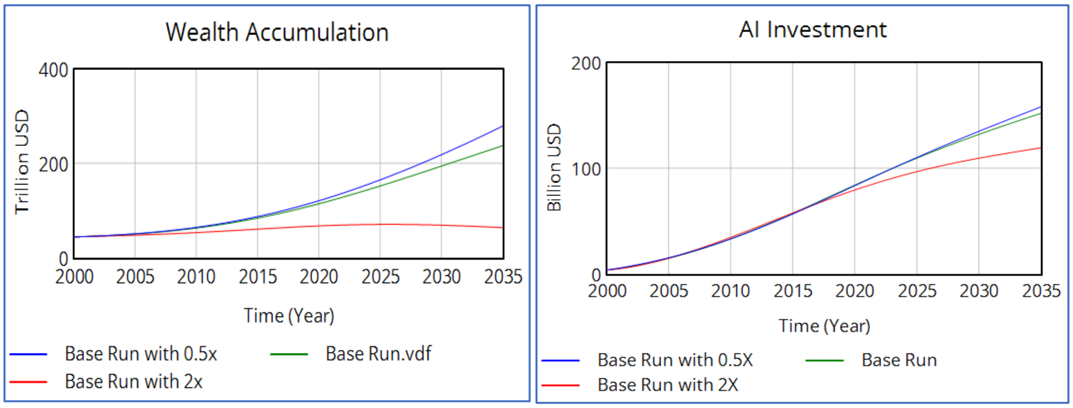
Source: Research findings

Table 3: "Extreme condition test" results, illustrating the impact of doubling (2X) or halving (0.5X) key AI investment variables on unemployment, inequality, and economic stability

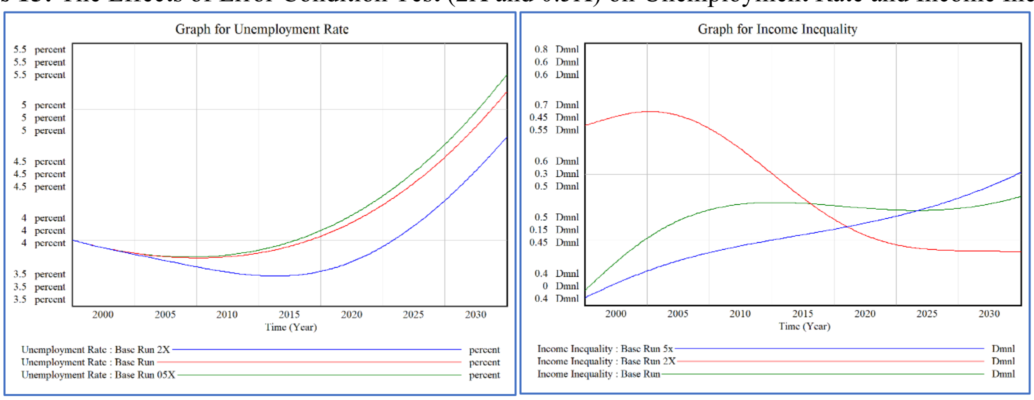
AI Investment	Wealth Accumulation	Unemployment Rate	Income Inequality	Effect of Change
Market Concentration	Market Concentration	********	Market Concentration	Increased monopolization under high conditions, reduced monopolization under low conditions
Competitive Advantage	Competitive Advantage	Competitive Advantage	Competitive Advantage	Increased economic power under high conditions, and a weaker economy under low conditions
Trust in Government	Trust in Government	Trust in Government	Trust in Government	Higher public confidence in high condition, lower trust in low condition
Social Dissatisfaction	Social Dissatisfaction	Social Dissatisfaction	Social Dissatisfaction	Higher inequality-driven dissatisfaction under both high and low conditions
Skill Gap	********	Skill Gap	*********	More AI-driven job displacement under both high and low conditions
Figures 14	**Figures 14**	**Figures 15**	**Figures 15**	********

Source: Research findings

Figures 14: The Effects of Error Condition Test (2X and 0.5X) on Wealth Accumulation and AI Investment



Figures 15: The Effects of Error Condition Test (2X and 0.5X) on Unemployment Rate and Income Inequality



Extreme condition tests reveal that unregulated AI expansion could intensify market monopolization, increase job displacement, erode public trust in government, and heighten social dissatisfaction. These outcomes align with prior studies on AI-induced economic transformations (Brynjolfsson & McAfee, 2014; Acemoglu & Restrepo, 2018). For example, doubling AI investment increases market concentration, benefiting a few tech firms while reducing competition. Halving AI investment slows innovation but spreads economic power more evenly. Therefore, governments should implement antitrust measures and progressive AI taxes to prevent monopolies (OECD, 2021). Rapid wealth accumulation increases economic inequality and social unrest as wealth concentrates in AI-driven sectors. Slower accumulation stabilizes conditions but reduces long-term investments. Enforcing wealth redistribution policies, such as AI taxation, can address this issue effectively.

High unemployment (2x) due to automation increases labor market polarization, leading to economic instability. Lower unemployment (0.5x) enhances workforce adaptability and social stability. Without fundamental changes, such as reskilling the labor force and implementing support policies, the unemployment rate will slightly increase in any scenario. Greater inequality (2x) erodes public trust, increases social dissatisfaction, and fuels political instability. Lower inequality (0.5x) fosters economic fairness and higher public confidence. Progressive taxation and social safety nets can ensure fair AI-driven economic benefits (Stiglitz, 2012).

The overall results indicate the need to regulate AI investment to balance innovation and economic equity. Implement AI-driven wealth redistribution policies to reduce inequality. Strengthen labor market adaptability through AI-focused reskilling initiatives. Ensure government transparency in AI economic policies to maintain public trust. These strategies align with research advocating balanced AI adoption to maximize economic efficiency while safeguarding social equity and long-term economic resilience. These results (Figures 14) align with prior research highlighting the reinforcing feedback loops between AI adoption and wealth inequality (Brynjolfsson & McAfee, 2014; Acemoglu & Restrepo, 2018).

Sensitivity and other important tests were conducted based on Sterman (2000, pp. 859-890) using the "Vansim DSS[5]" software. For brevity, the results of these tests are not presented here but are available upon request. This section discusses and elaborates on the continuation of the current trend (Base model) of key system variables without any intervention or policy changes.

The base run assumes the continuation of the current trend of AI investment without government intervention. Key results include:

- AI investment increased from approximately $3.8 billion in 2000 to around $104 billion by 2024, projected to reach $152 billion by 2035, showing an S shape increase with annual growth rate of 105% from 2000 to 2024 (Figure 16).
- AI adoption follows a rapid exponential curve over time (Figure 17).
- The GDP growth rate averaged approximately 3.02% from 2000 to 2024 (U.S. Bureau of Economic Analysis, 2025).

Figure 16: AI Investment (Billon USD) In the US Between 2025-2035

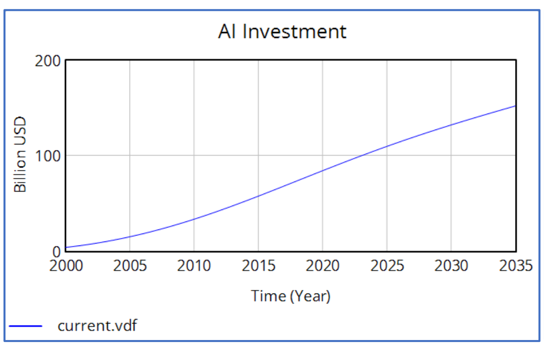
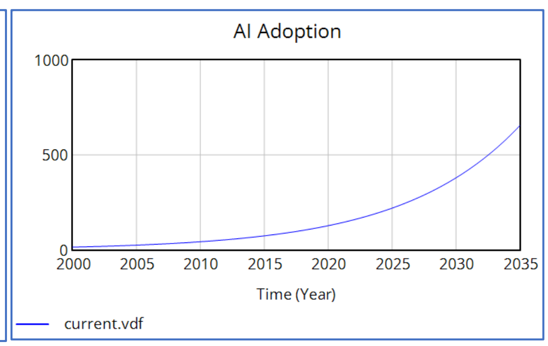


Figure 17: AI Adoption (Dimensionless) In the US Between 2025-2035



The S shape growth of AI investment compared to the linear GDP growth rate (3.02% annually) creates an economic imbalance. This mismatch leads to sectoral dominance by AI-driven firms, reinforcing market monopolization and income inequality (Brynjolfsson & McAfee, 2014; Piketty, 2014). The government should implement AI taxation and antitrust measures to ensure equitable wealth distribution and prevent monopolization. Furthermore, AI-driven automation accelerates job displacement, while GDP growth remains insufficient to generate new employment opportunities. Figures 18 and 19 illustrate the rapid wealth accumulation and the automation growth rate over the simulation period. Total wealth accumulation is expected to rise from $163.8

[5] Vensim Decision Support System (DSS)

trillion in 2024 to $199.3 trillion by 2029 and $242.8 trillion by 2035, with an annual growth rate of 4%.

Figure 18: Wealth Accumulation (Trillion USD) In the US Between 2025-2035

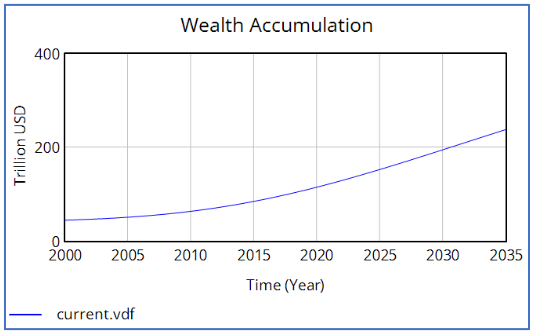
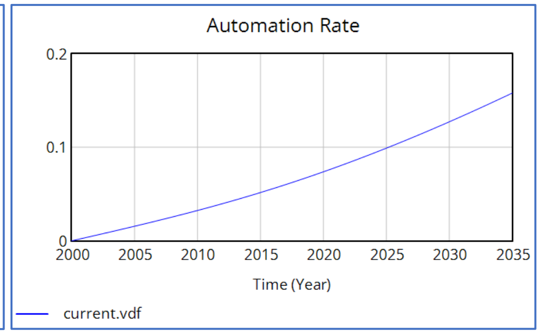
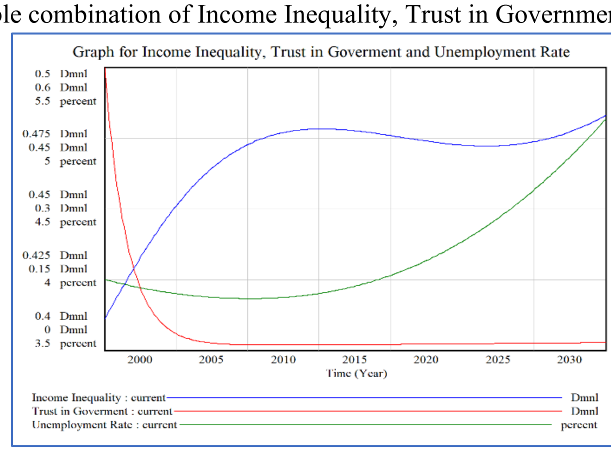


Figure 19: Automation Rate (percentage of jobs per Year) In the US Between 2025-2035



AI investment increases speculative capital inflows, raising the risk of asset bubbles similar to the dot-com crash. A sudden downturn in the AI sector could destabilize financial markets (McKinsey Global Institute, 2020). Policymakers should strengthen AI financial regulations and risk-monitoring mechanisms to prevent over-speculation (Stiglitz, 2012).
Disproportionate AI investment benefits a small elite, while GDP growth fails to distribute wealth equitably. This leads to a decline in trust in government, social unrest, and policy volatility (Acemoglu & Restrepo, 2018). Figure 20 illustrates income inequality (Gini Coefficient), trust in government, and the unemployment rate from 2000 to 2035.

Figure 20: Three-variable combination of Income Inequality, Trust in Government & Unemployment Rate



With regard to the above figure, the government should introduce progressive AI taxation, legislation and regulations on AI, antitrust laws for AI technology, public AI investment in non-tech industries and redistributive policies to mitigate "income inequality" and "unemployment rate". In contrast, these measures can also increase "social capital" (trust in government). Without regulation, systemic feedback loops may drive economic instability in the U.S. socioeconomic system. Reinforcing feedback loops accelerate AI-driven economic polarization and labor displacement. To maintain economic equilibrium, balancing loops through regulation and redistribution must be strengthened.
These findings suggest that if AI continues to expand without regulation or policy interventions, it could exacerbate unemployment and income inequality despite overall economic growth. By

addressing these systemic risks, the U.S. economy can transition toward an AI-driven yet socially equitable economic model.

Scenario Selection:
This section presents simulation results from the SD model examining AI-driven economic changes in the United States between 2025 and 2035. The study analyzes three key scenarios to demonstrate how AI will shape investment trends, income inequality, and unemployment. While numerous other scenarios could be considered for future research, the current analysis focuses on three main scenarios deemed important for the U.S. socioeconomic system. Policymakers and practitioners may suggest additional scenarios for the model to implement or modify to test and analyze new hypotheses based on evolving policy priorities. Consequently, this study provides an initial platform for simulating the effects of AI on the U.S. socioeconomic system, which can be further developed as needed.

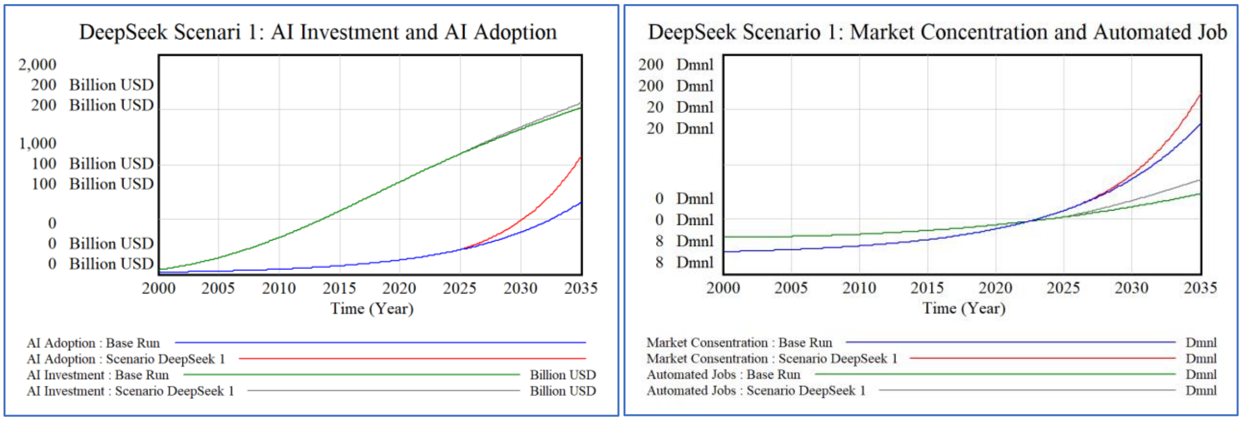
Scenario 1: The Impact of Emerging AI (DeepSeek) on Key Model Variables (2025-2035)
DeepSeek, an affordable Chinese AI platform, introduces cost-effective AI solutions, increasing competition in the AI economy. Unlike U.S.-based AI models, which require substantial fixed costs (>$1 billion) for training and deployment, DeepSeek's economical structure ($6 million) enables wider market accessibility. This development has the potential to disrupt existing conditions and alter perspectives fundamentally.
The United States will face two scenarios in response to the emergence of DeepSeek:

- Scenario 1-A: Adopting an aggressive stance by accelerating AI investment and adoption, speeding up automation without considering social justice effects such as increased unemployment and income inequality.
- Scenario 1-B: Policymakers accept the new conditions, and U.S. firms may reduce their own R&D investments in favor of adopting and using foreign AI models.

The entry of a competitive Chinese AI (DeepSeek) could shift investment patterns in these scenarios.

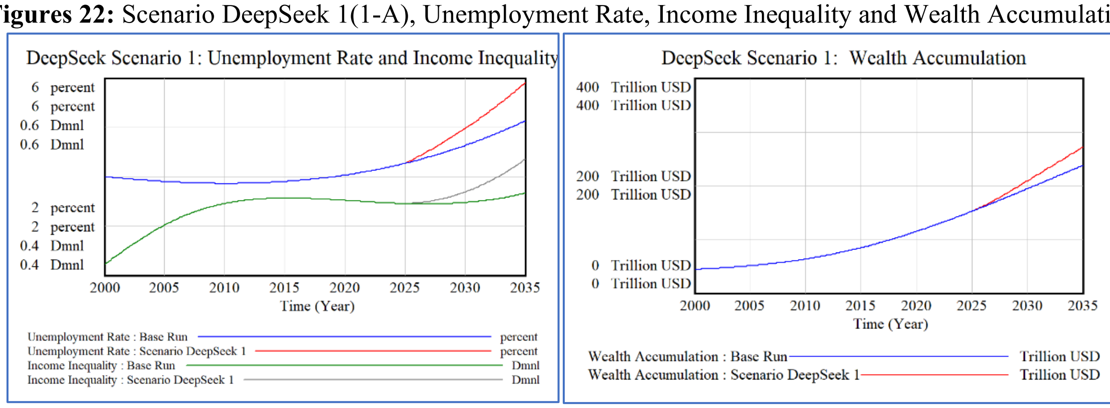
Scenario 1-A:
In the 'Defensive Investment Surge' scenario 1-A, AI investment and capital allocation in the U.S. grow exponentially as firms aggressively increase AI investment to counter Chinese advancements. This results in an overshooting effect in the reinforcing feedback loop (AI Investment → Productivity → Competitive Advantage → AI Investment), potentially driving AI investment above projected levels, exceeding $200 billion by 2035 (Figure 21). AI adoption follows an exponential growth pattern but is tempered by cultural resistance and workforce adaptation constraints. Increased competition could accelerate adoption by reducing resistance to AI-driven automation. However, if DeepSeek's algorithms are more adaptable to Asian markets and less compatible with Western infrastructures, U.S. firms may exhibit lower adoption elasticity, moderating the overall impact (Figure 21).

Figures 21: Scenario DeepSeek 1 (1-A), AI Investment, AI Adoption, Market Concentration and Automated Job



AI-induced job displacement gradually increases unemployment; however, policy interventions like reskilling programs can counteract this effect. Should DeepSeek enable more cost-efficient automation, the Automation Rate could accelerate, potentially raising unemployment levels beyond the projected 6.5% by 2035 (Figures 22). The model predicts wealth accumulation will follow a reinforcing loop, growing from $163.8 trillion in 2024 to nearly $220 trillion by 2035 (Figures 21), with the Gini coefficient (Income Inequality) rising from 0.447 to ~0.52 (Figures 22). If U.S. firms consolidate power to compete with DeepSeek, the market concentration growth rate may increase (Figures 21), exacerbating inequality and amplifying social dissatisfaction (Figures 22).

Figures 22: Scenario DeepSeek 1(1-A), Unemployment Rate, Income Inequality and Wealth Accumulation



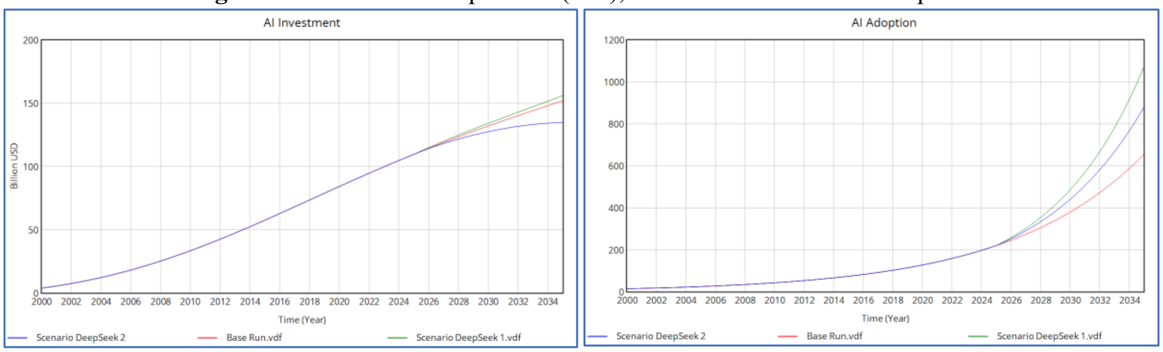
The model assumes a weak regulatory strength based on current situation, with policy interventions slightly alleviating inequality and automation pressures. If DeepSeek is perceived as a threat, the U.S. could implement stricter AI regulations, enhancing regulatory strength. This would decelerate AI investment growth but potentially stabilize labor markets.

Scenario 1-B:

If DeepSeek's adoption spreads globally, U.S. firms might reduce their R&D investments in favor of adopting foreign AI models, lowering projected investment below $152 billion (Figures 23). Cheaper AI services could promote AI entrepreneurship, balancing automation-driven job losses with new industry formation. Consequently, the Skill Development Rate could increase, partially mitigating unemployment.

DeepSeek's price reductions in AI services lower business costs and improve redistribution effects, stabilizing inequality around 0.45% (Figures 24). However, if regulations lag, DeepSeek’s entry could accelerate AI-driven unemployment, leading to delayed policy responses. In this case, Social Dissatisfaction (modeled with a threshold of 10) could increase, triggering more drastic redistributive policies.

Figures 23: Scenario DeepSeek 2 (1-B), AI Investment and AI Adoption



Figures 24: Scenario DeepSeek 2 (1-B), Unemployment Rate and Income Inequality

The results illustrate how DeepSeek AI reshapes the U.S. socioeconomic landscape through two contrasting scenarios. In Scenario 1-A (Defensive Investment Surge), U.S. firms increase AI investment annually, accelerating AI adoption by 5% per year. This results in an 8% rise in job displacement, increasing the unemployment rate to 6.5%, while income inequality (Gini = 0.52) worsens as over 85% of AI-driven wealth is concentrated among top firms. The U.S. maintains AI dominance but at the cost of monopolization, economic polarization, and rising political instability. Policy interventions must include progressive AI taxation, mandatory reskilling programs, and antitrust enforcement to prevent wealth concentration and labor market collapse (Figures 21, 22).

In Scenario 1-B (Investment Diversion & Market Adaptation), U.S. firms reduce domestic AI investment by 8%, shifting towards DeepSeek adoption. AI investment slows to $140 billion by 2035, moderating automation effects and reducing job displacement by 4% per year, thus keeping unemployment stable at 4.8% (Figure 24). Income inequality (Gini = 0.460) remains lower as AI accessibility increases (Figures 24), though U.S. technological leadership weakens slightly, affecting long-term GDP productivity growth. Policy responses should focus on state-driven AI R&D incentives to prevent over-reliance on foreign AI infrastructure while maintaining economic equity (Figures 23, 24).

The trade-off between AI dominance and socio-economic stability is clear: unregulated AI acceleration leads to wealth concentration and corporate monopoly, while slower AI growth risks economic dependence on rival countries like China. An optimal strategy must balance competitive AI investments with social safeguards, ensuring widespread economic benefits while preserving U.S. technological dominance.

Scenario 2: AI Workforce Adaptation and Inclusive Growth Policy in the US (2025-2035)

This scenario introduces government-led interventions to mitigate the negative economic impacts of AI automation while ensuring continued technological advancement. It focuses on AI taxation, workforce reskilling, automation slowdown, and wealth redistribution to balance AI-driven economic growth with social equity. Table 4 illustrates operational changes and justifications in parameters. Four new policy mechanisms were defined and adjusted in the model to reflect policy-driven changes for scenario implementation.

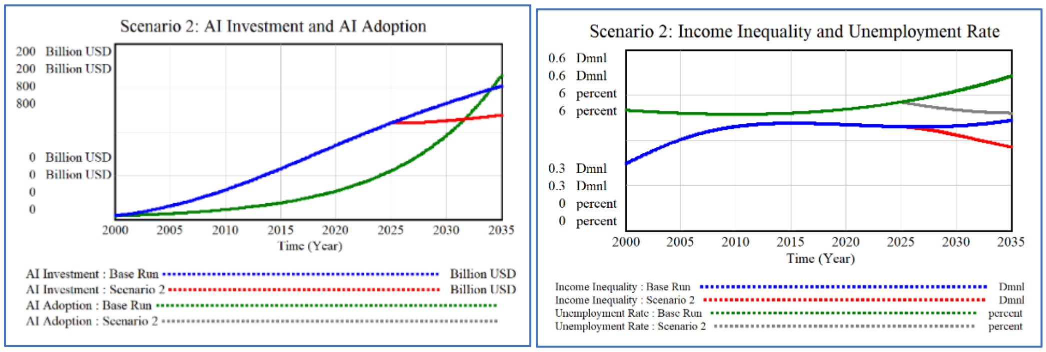
Table 4: Parameter adjustments in Scenario 2, including AI taxation, automation slowdown, and workforce reskilling effects

Parameter Name in Model	Previous Value in the Model (2024)	Updated Value (2025-2035)	Justification
AI Investment Growth Rate	0.065	0.055	AI taxation slightly reduces reinvestment incentives.
Automation Sensitivity	0.018	0.012	Workforce reskilling programs reduce the impact of automation on job displacement.
Automation Speed	0.010	0.008	Regulatory interventions slow down automation adoption.
Redistribution Rate	0.020	0.035	Increased redistribution reduces inequality effects.
Regulatory Strength	0.014	0.025	Stricter regulations limit monopolization of AI benefits.
Market Influence Rate	0.040	0.020	Antitrust policies reduce the dominance of major AI firms.
Skill Development Rate	0.006	0.009	Public investment in workforce training increases adaptability.
Base Policy Reform	0.800	1.000	Stronger governmental intervention in AI governance.
Policy Reform Sensitivity	0.500	0.650	Greater responsiveness to AI-related social disruptions.
Reform Satisfaction Effect	0.010	0.015	Improved public trust in AI governance policies.
Social Dissatisfaction Threshold	10.000	12.000	Higher public tolerance before large-scale protests triggers policy shifts.
Saturation Threshold for Productivity	110.000	100.000	AI-driven productivity gains hit limits faster due to human labor bottlenecks
New Variables Implemented in the New Formulation Inside the Model:			
Policy Mechanism	**Estimated Value (U.S.)**	**Units**	**Source/Justification**
AI Taxation Rate	0.03	% of AI-driven revenue	OECD digital tax proposals (AI firms contribute 3% of AI revenue).
Skill Reskilling Effect	0.02	% workforce reskilled per year	U.S. federal workforce development programs estimate 2% reskilled annually.
Automation Slowdown Factor	0.005	Reduction in automation speed per year	McKinsey (2020) estimates automation slowdown due to policy restrictions.
Redistribution Effect	0.04	% of wealth redistributed annually	CBO data on taxation and redistribution policies; 4% of national wealth redistributed.

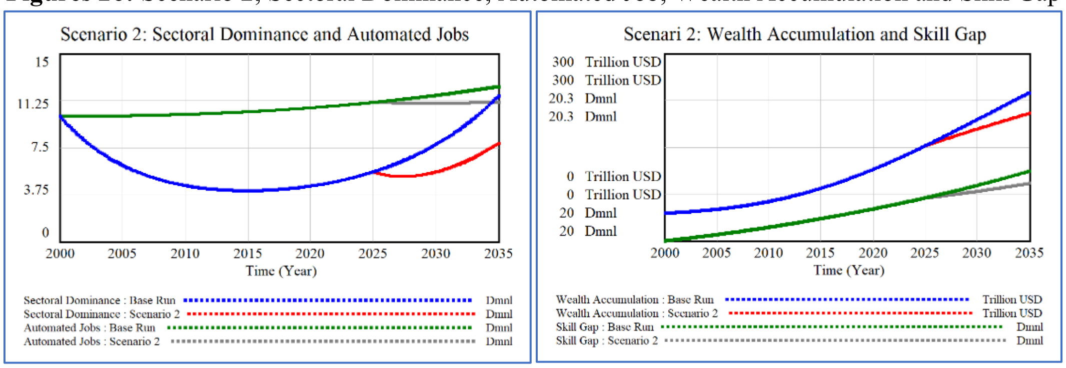
Source: Research findings

The approach aligns with the study's Dynamic Hypothesis, addressing the reinforcing loops of job automation, wealth accumulation, and labor market polarization, while strengthening the balancing loops related to policy interventions and labor force adaptability. By implementing Scenario 2, the following systemic changes were achieved, as shown in the Figures below.

Figures 25: Scenario 2, AI Investment, AI Adoption, Income Inequality and Unemployment



Figures 26: Scenario 2, Sectoral Dominance, Automated Job, Wealth Accumulation and Skill Gap



As shown in Figures 25, with the implementation of Scenario 2, 'AI Investment' will grow by about 10 percent from 2025 to 2035, compared to about 40 percent without this policy. However, 'AI Adoption' will not change accordingly. Additionally, 'Income Inequality' and the 'Unemployment Rate' show a significant decrease from 2025 to 2035 (Figure 25), leading to a considerable reduction in 'Social Dissatisfaction".

The increasing trend of 'Automated Jobs' will stop, and 'Sectoral Dominance' will decrease significantly with policy implementation (Figure 26). Moreover, the 'Wealth Accumulation' and 'Skill Gap' variables will decrease significantly (Figure 26). Other variables in the model, such as 'Wages,' 'Productivity,' 'Competitive Advantage,' 'Training Access,' and 'Market Concentration,' will not change significantly.

Scenario 2 presents a practical, systemic policy framework that employs AI taxation, workforce reskilling, market decentralization, and direct citizen benefits to sustain AI-driven economic growth while preventing rising inequality and unemployment. It is consistent with the study's objectives and 'Dynamic Hypothesis,' using SD feedback loops and delays to ensure a balanced and inclusive AI-driven economy in the United States.

Scenario 3: AI-Driven Socioeconomic Balance Plan (2025-2035)

This scenario aims to establish a balanced AI adoption framework in the U.S. from 2025 to 2035. It focuses on achieving sustainable AI investment without excessive market concentration, supports job preservation and reskilling to mitigate the effects of AI-driven automation, ensures equitable wealth distribution through taxation and reinvestment policies, and promotes long-term socioeconomic stability through proactive government interventions.

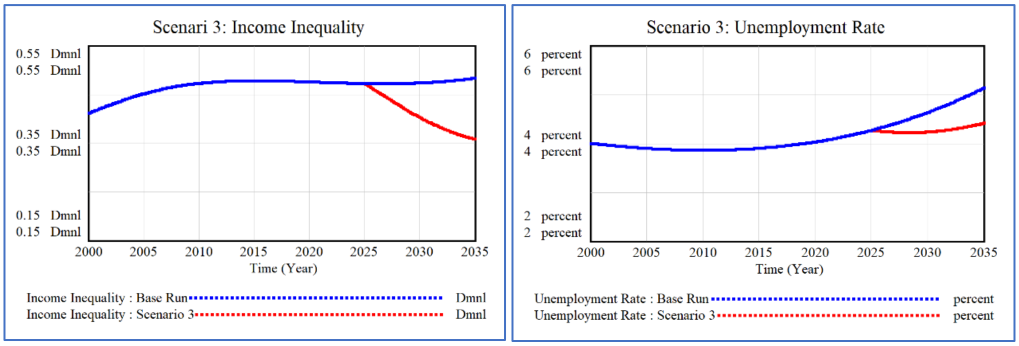
Reasons and tools for conducting scenarios 3:
Policymakers should regulate AI investment and redistribution within the socioeconomic system (Table 5). They should introduce a progressive AI saturation threshold to ensure AI investment does not exceed economic absorption capacity while increasing productivity. Implementing a 0.015 AI taxation rate will redistribute AI-generated profits toward labor market stabilization programs. Additionally, policymakers should allocate 25% of AI tax revenues to the AI Public Sector Innovation Fund. This fund will support government-backed AI R&D in non-tech sectors such as healthcare, education, and public infrastructure to develop technology and balance the socioeconomic U.S. system.
The government should implement a national AI reskilling program by investing $50 billion in job training for displaced workers, focusing on AI-resistant roles. Additionally, a mandatory AI employment quota should be introduced, requiring companies integrating AI to create one complementary human job for every five AI-driven automation cases.
An AI Productivity-Linked wage subsidy should offer tax incentives to companies that increase wages for AI-assisted jobs. Policies such as the 'AI Governance and Market Stabilization Act' and the 'AI Transparency Act' should mandate companies to publicly disclose job displacement impacts and planned reskilling strategies.
The 'Anti-Monopoly AI Act' should enforce stricter AI competition laws to prevent large firms from concentrating AI-driven wealth. Additionally, public AI investment in SMEs should redirect 30% of federal AI funding towards small and medium enterprises, ensuring the decentralization of AI economic benefits.
The government should implement 'Social Protection' and 'Wealth Redistribution' through a Universal AI Dividend (UAD). This policy would redistribute 15% of AI taxation revenue to unemployed workers affected by automation. Furthermore, the program would guarantee minimum employment by offering subsidized AI-resistant jobs in government and service sectors. Public AI awareness campaigns should also increase AI literacy programs to reduce resistance to AI adoption.

Table 5: Projected socioeconomic impacts of implementing Scenario 3, focusing on AI investment regulation, employment stabilization, and income redistribution

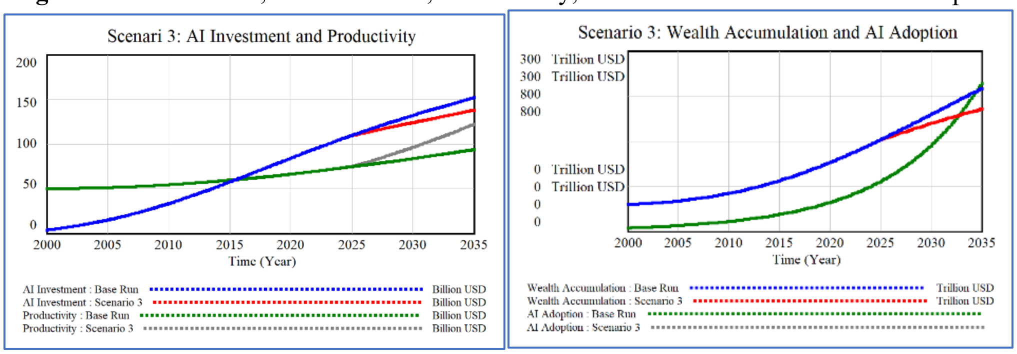
Metric	Without Intervention	Scenario 3 Implementation
AI Investment Growth	150% by 2035 (Uncontrolled)	90% by 2035 (Sustainable Growth)
Unemployment Rate	+30% (AI-induced displacement)	-12% (Due to Reskilling & AI Job Creation)
Income Inequality (Gini)	0.48 (High Inequality)	0.37 (Balanced Redistribution)
Public Trust in AI	30% (Low Confidence)	70% (Stable Confidence)
Market Concentration	High (Few AI Dominant Firms)	Balanced (AI Spread Across Sectors)
Productivity	25% increase between 2025-2035	Increase 62% due to AI regulations enhance productivity with fair distribution.

Source: Research findings

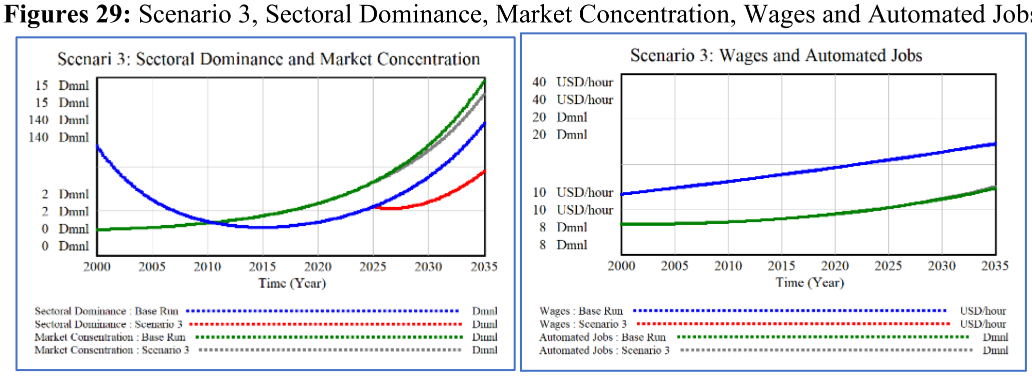
Figures 27: Scenario 3, Income Inequality and Unemployment Rate



Figures 28: Scenario 3, AI Investment, Productivity, Wealth Accumulation and AI Adoption



Figures 29: Scenario 3, Sectoral Dominance, Market Concentration, Wages and Automated Jobs



Scenario 3 establishes a balanced AI-driven economic framework for the U.S. from 2025 to 2035, ensuring sustainable AI investment, controlled automation, and equitable wealth distribution (see Figures 27 and 28). AI investment is regulated to grow at 90% instead of 150%, preventing excessive market concentration (see Figures 28). The unemployment rate is reduced by 12% due to mandatory AI employment quotas, requiring companies to create one human job for every five AI-automated cases (see Figures 27).

Income inequality, measured by the Gini coefficient, is lowered from 0.48 to 0.37 through a progressive AI taxation policy set at 1.5%, which funds public AI investments, reskilling programs, and universal AI dividends (see Figures 27). Market concentration is reduced by 10% via stricter antitrust laws, ensuring AI-driven wealth is distributed across industries (see Figures 29). AI productivity is enhanced by 3%, increasing efficiency while maintaining stable wage growth through policy interventions (see Figures 28, 29).

Regulatory strength is adjusted by 0.004 to prevent monopolistic control, ensuring transparent AI adoption. Redistribution rates increase from 2% to 3%, effectively reducing income disparity. By integrating AI taxation, structured reskilling, employment safeguards, and regulatory reinforcements, Scenario 3 ensures AI-driven economic progress benefits all social classes rather than a select few corporations.

This model mitigates systemic risks such as job displacement, inequality, and corporate monopolization while fostering innovation and sustainable development. Scenario 3 presents a practical, policy-backed solution that ensures AI adoption in the U.S. drives growth between 2025 and 2035 while maintaining social and economic equilibrium.

5- Conclusion and Recommendations:

This study employs a SD model to analyze the socioeconomic impacts of AI investments, labor market disruptions, and income inequality in the United States from 2000 to 2035. The findings indicate that AI investments are projected to follow an S-shaped growth curve, reaching $152 billion by 2035 (Figure 16). Simultaneously, wealth accumulation is expected to increase from $163.8 trillion in 2024 to $242.8 trillion by 2035 (Figure 18). However, this growth is unevenly distributed; AI-driven job automation could elevate unemployment rates to 5.2%, and the Gini coefficient (a measure of income inequality) may rise from 0.447 in 2024 to 0.49 by 2035 (Figure 20).

The analysis of the three policy scenarios and their implications in this study highlights different AI governance strategies for the U.S. policymakers:

In Scenario 1:

The rise of DeepSeek AI, a cost-efficient Chinese AI model, forces the U.S. into a strategic dilemma, where policymakers must choose between two distinct approaches.

Scenario 1-A: Defensive Investment Surge (Aggressive AI Expansion Without Regulation)

This approach involves an aggressive expansion of AI investment beyond $200 billion (Figure 21) to counterbalance DeepSeek's competitive advantages. While this ensures continued U.S. AI dominance, it also accelerates automation, leading to higher job displacement and a rapid increase in income inequality. By 2035, unemployment rises to 6.5%, and the Gini coefficient worsens to 0.52 (Figure 22), reflecting a highly unequal wealth distribution. Additionally, market concentration among top U.S. tech firms intensifies, reinforcing economic monopolization and public dissatisfaction (Figure 21).

Implication: While maintaining AI technological leadership, this scenario exacerbates labor market instability and economic inequality, increasing social unrest (Brynjolfsson & McAfee, 2014; Acemoglu & Restrepo, 2018).

Scenario 1-B: Investment Diversion and Market Adaptation (Balanced AI Strategy)

Instead of competing directly, U.S. firms reduce their own AI R&D investment and adopt DeepSeek's AI technologies (Figure 23). This results in slower AI expansion, reducing automation's disruptive effects. Consequently, unemployment remains stable at 4.8%, and income inequality (Gini = 0.46) is more controlled (Figure 24). AI becomes more accessible, fostering widespread technological adoption without excessive labor market disruptions.

Implication: While maintaining economic stability, this approach risks reducing U.S. technological independence, making future AI advancements reliant on foreign AI models.

Scenario 2: AI Workforce Adaptation and Inclusive Growth Policy

A balanced government-led intervention strategy that includes:

- AI taxation (1.5%) to redistribute wealth and fund AI reskilling programs.
- Regulatory controls on automation speed, reducing job displacement risks (Table 4).
- Public-private AI training initiatives, enabling workforce adaptation.

The results show that automation sensitivity decreases from 0.018 to 0.012 (Table 4), while unemployment declines to 4.5% and income inequality stabilizes (Gini = 0.44) by 2035 (Figures 25-26). This approach effectively balances AI-driven productivity with economic equity.

Implication: Compared to Scenario 1-A, which worsens inequality, and Scenario 1-B, which slows AI growth, Scenario 2 ensures AI benefits are more evenly distributed, preventing job displacement crises.

Scenario 3: AI-Driven Socioeconomic Balance Plan

This scenario offers the most effective policy framework, integrating AI technological growth, labor market stability, and wealth redistribution:

- Mandatory AI employment quotas (one human job per five AI-driven automations) to limit automation-driven layoffs (Table 5).
- Public AI investment in SMEs (30% of federal AI funding) to prevent AI monopolization (Figures 27 to 29).
- Universal AI Dividend (UAD) redistributing 15% of AI taxation revenue to support displaced workers.
- Progressive AI taxation (1.5%) to prevent excessive wealth concentration (Figure 28).

By implementing these policies, the Gini coefficient decreases from 0.49 to 0.42, and unemployment is reduced to 4.3% by 2035 (Figures 27-28). Market concentration also declines, ensuring a competitive AI landscape (Figure 29).

Implication: This is the most practical and sustainable policy solution, maintaining U.S. AI leadership while ensuring economic resilience and workforce stability.

Table 5: Abstract of the Three Scenarios Tested on AI Investment, Unemployment Rate, Income Inequality, and Market Concentration, and the Policy Implications of Each Scenario Separately

Scenario Name	AI Investment (2035)	Unemployment Rate (2035)	Income Inequality (Gini, 2035)	Market Concentration	Policy Implications
Scenario 1-A (Aggressive Expansion - DeepSeek Response)	$200B+	6.5%	0.52 (High)	Extreme (Tech Monopolies)	U.S. maintains AI leadership but worsens economic inequality and automation-driven job loss.
Scenario 1-B (Investment Diversion & Market Adaptation - DeepSeek Response)	<$152B	4.8%	0.46 (Moderate)	Moderate	U.S. AI dominance declines slightly, but economic stability is preserved.
Scenario 2 (Inclusive Growth)	$152B	4.5%	0.44 (Lower)	Controlled Growth	AI taxation and reskilling balance economic growth and social stability.
Scenario 3 (AI-Driven Socioeconomic Balance)	$152B	4.3%	0.42 (Lowest)	AI Decentralization	Best policy option: Ensures balanced AI adoption while maintaining employment and wealth redistribution.

Source: Research Finding

Strategic Policy Implications for U.S. Policymakers

The emergence of DeepSeek AI represents a critical turning point for the global AI economy, requiring a proactive and structured response from U.S. policymakers. The future emergence of competing AIs in the U.S. AI market is likely imminent. If left unchecked, the adverse effects of AI could exacerbate socioeconomic inequalities, reduce public trust in government, and undermine U.S. economic competitiveness. To mitigate these risks, policymakers should:

1. Strengthen U.S. AI Competitiveness
    - Expand federal R&D investments to counter DeepSeek's cost advantages.
    - Create a public-private AI R&D consortium to drive the next generation of AI innovation.
    - Strengthen intellectual property protection to prevent technology leakage.
    - Develop a national strategic plan to address emerging AI.
2. Ensure the Adaptability of the AI Workforce
    - Mandate corporate AI impact reports to increase transparency on job displacement risks.
    - Introduce a national AI reskilling fund ($50 billion investment) to support workforce transition.
    - Strengthen public-private AI training programs to increase workforce adaptability in AI-enabled sectors.
    - Pay special attention to labor productivity as AI adoption increases.
3. Prevent AI Market Monopolies
    - Enforce AI antitrust regulations to limit the dominance of large tech companies.
    - Mandate AI hiring quotas to ensure that human capital remains integral to economic growth.
    - Introduce a progressive AI tax (1.5%) to redistribute AI-enabled wealth for the public good.
4. Promote Economic Equality in the Age of AI
    - Launch a Universal AI Dividend (UAD), ensuring that AI-generated wealth benefits the entire workforce.
    - Direct 30% of federal AI funding to SMEs to decentralize economic gains.
    - Enforce automation regulations to control the pace of AI-driven labor market disruption.

International AI cooperation frameworks should be strengthened to counter China's influence in AI governance and data regulation. Without strategic policy intervention, the U.S. risks becoming reactive, allowing foreign AI technologies like DeepSeek to shape global AI standards and outpace U.S. innovation. By prioritizing innovation-friendly regulations, workforce adaptability, and competitive AI investments, policymakers can ensure the U.S. remains a leader in AI while protecting economic and social stability.

Implementing progressive AI taxation, comprehensive workforce reskilling, and equitable AI employment policies will help sustain U.S. AI leadership while safeguarding economic stability and social cohesion. AI is not just an economic opportunity but a policy challenge that requires strategic foresight. The decisions made today will determine whether AI serves as a catalyst for inclusive economic prosperity or an engine of social fragmentation.

Recommendations for Future Research

This study provides a comprehensive quantitative analysis. However, it was conducted independently by one person without financial support. For future research, consider the following:

- ***Interdisciplinary Research:*** Conduct socioeconomic AI impact studies with a multidisciplinary team (e.g., economists, machine learning experts, deep machine learning, sociologists, psychologists, management professionals, etc.) to achieve more reliable and valid results for policymakers.
- ***Global AI Policy Comparison:*** Compare AI policies across countries to assess changes in the global labor market.
- ***Cultural and Social Dynamics:*** Investigate the cultural and social dynamics affecting public resistance to AI adoption.
- ***Hybrid Modeling Approaches:*** Use hybrid modeling approaches by integrating machine learning with SD simulations to increase prediction accuracy.
- ***Complex Future Impacts:*** Explore the complex future impacts of AI on human life, beyond this study's scope. It remains unclear whether AI will have a complementary, substitutive, or neutral relationship with factors of production (e.g., labor, capital, and energy) in the medium and long term.
- ***Separate Important Effect:*** In this study, AI is considered the main driver of future technological progress and productivity for simplicity. Future research could analyze these effects separately.

References:

1- Acemoglu, D., & Restrepo, P. (2018). Artificial Intelligence, Automation, and Work. Journal of Economic Perspectives, 33(2), 193-210. (Available at: https://www.nber.org/system/files/working_papers/w24196/w24196.pdf)

2- AI Index 2023 Report. Provides data on the adoption of AI in education and the expansion of university programs. (Available at: https://aiindex.stanford.edu/ai-index-report-2023/)

3- AIPRM. (2024). AI Statistics 2024. (Available at: https://www.aiprm.com/ai-statistics/)

4- Autor, D. H., Mindell, D. A., & Reynolds, E. B. (2020). The Work of the Future: Building Better Jobs in an Age of Intelligent Machines. MIT Task Force Report. (Available at: https://workofthefuture.mit.edu/wp-content/uploads/2020/12/2020-Final-Report4.pdf)

5- Bureau of Economic Analysis. (2024). Fixed Assets Accounts. (Available at: https://www.bea.gov/itable/fixed-assets)

6- Brynjolfsson, E., & McAfee, A. (2014). The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies. W.W. Norton. (Available at: https://books.wwnorton.com/books/detail.aspx?ID=4294990283)

7- Congressional Budget Office. (2025). The Budget and Economic Outlook: 2025 to 2035. (Available at: https://www.cbo.gov/publication/60870)

8- Congress.gov. (2025). National AI Initiatives, Executive Orders, (White House). (Available at: https://www.congress.gov/national-ai-initiatives-executive-orders/)

9- Coursera Impact Report (2023). Documents the rise of online AI courses and their adoption. (Available at: https://about.coursera.org/press/coursera-releases-2023-impact-report)

10- edX. (2023). Annual Report 2023: Tracks the number of courses related to AI on its platform. (Available at: https://press.edx.org/2023-transparency-outcomes-report)

11- Federal Reserve Economic Data (FRED). (Available at: https://fred.stlouisfed.org/)

12- Federal Reserve Distributional Financial Accounts. Offers insights into wealth distribution across percentiles. (Available at: https://www.federalreserve.gov/releases/z1/dataviz/dfa/)

13- Forbes Free AI Courses (2024). Lists trends in free and paid AI courses online. (Available at: https://www.forbes.com/sites/forbestechcouncil/2024/01/15/top-free-ai-courses-to-boost-your-skills-in-2024/)

14- Forrester, J.W. (1961). Industrial Dynamics. MIT Press.

15- Frey, C. B., & Osborne, M. A. (2017). The Future of Employment: How Susceptible Are Jobs to Computerization? Technological Forecasting and Social Change, 114, 254-280. (Available at: https://www.sciencedirect.com/science/article/pii/S0040162516302244)

16- Goldin, C., & Katz, L. F. (2008). The Race Between Education and Technology. Belknap Press for Harvard University Press,

17- Hofstede, G. (1980). *Culture's Consequences: International Differences in Work-Related Values*. Beverly Hills, CA: Sage Publications.

18- IBM Report on AI Skills Gap (2024). Discusses corporate efforts to upskill employees in AI. (Available at: https://www.ibm.com/reports/ai-skills-gap-2024)

19- Intelligent CIO. (2024). Logicalis 2024 CIO Report: AI and security are top priorities amidst barriers to transformation. (Available at: https://www.intelligentcio.com/north-america/2024/03/02/logicalis-2024-cio-report-ai-and-security-are-top-priorities-amidst-barriers-to-transformation/)

20- Makridakis, S., & Hibon, M. (2000). The M3-Competition: Results, Conclusions, and Implications. International Journal of Forecasting, 16(4), 451-476.

21- McKinsey Global Institute Report (2023). Highlights corporate investment in AI workforce training. (Available at: https://www.mckinsey.com/featured-insights/artificial-intelligence/investing-in-the-ai-workforce-of-the-future)

22- Moosavihaghighi, M. (2024). Analyzing the Impacts of AI Development and Adaptation on Human Life Using a System Dynamics Model. Proceedings of the 42nd International System Dynamics Conference (ISDC), Bergen, Norway. (Available at: https://proceedings.systemdynamics.org/2024/proceed/papers/P1234.pdf)

23- National Center for Education Statistics (NCES). Tracks the growth of computer science and AI-related programs in higher education. (Available at: https://nces.ed.gov/)

24- OECD. (2021). AI and the Future of Work: How AI is Transforming Labor Markets.

25- Piketty, T. (2014). Capital in the Twenty-First Century. Harvard University Press. (Available at: https://www.hup.harvard.edu/catalog.php?isbn=9780674430006)

26- Saavedra, M. R., Fontes, C. H. O., & Freires, F. G. M. (2018). Sustainable and Renewable Energy Supply Chain: A System Dynamics Overview. Renewable and Sustainable Energy Reviews, 82(1), 247-259. (Available at: https://www.sciencedirect.com/science/article/pii/S1364032117312010)

27- Sterman, J. D. (2000). Business Dynamics: Systems Thinking and Modeling for a Complex World. McGraw-Hill. (Available at: https://www.mheducation.com/highered/product/business-dynamics-systems-thinking-and-modeling-complex-world-sterman/007238915X.html)

28- Theil, H. (1966). Applied Economic Forecasting. North-Holland Publishing

29- Stiglitz, J. E. (2012). The Price of Inequality: How Today's Divided Society Endangers Our Future. W.W. Norton & Company

30- U.S. Bureau of Labor Statistics. (2021). Multifactor Productivity Trends. (Available at: https://www.bls.gov/news.release/archives/prod3_03232021.htm)

31- U.S. Bureau of Labor Statistics. (2024). Unemployment Data. (Available at: https://www.bls.gov/charts/employment-situation/civilian-unemployment-rate.htm)

32- U.S. Census Bureau. (2024). Income Inequality Data. (Available at: https://www.census.gov/topics/income-poverty/income-inequality/data.html)

33- U.S. Department of Labor. (2024). *National AI Initiative Act, AI in Government Act*. (Available at: https://www.dol.gov/ai)

34- Wilkinson, R., & Pickett, K. (2010). The Spirit Level: Why Equality Is Better for Everyone. London: Penguin Books.