Agent-Based Model for Predicting the Impact of Generative AI

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Abstract. Generative artificial intelligence (AI) systems have revolutionized various industries by autonomously generating content, mimicking human creativity. However, concerns about their social and economic consequences arise with widespread adoption. This paper explores these consequences using agent-based modeling (ABM), aiming to predict the impact of generative AI on societal frameworks. The ABM incorporates individual, business, and government agents, simulating education, skills acquisition, AI adoption, and regulation dynamics. Leveraging ABM, this study contributes to understanding AI's complex interactions, offering insights for policy-making processes. The literature review highlights ABM's efficacy in forecasting AI impacts. Results indicate AI adoption, employment, and regulation trends, suggesting potential policy implications. Future work involves refining the model, assessing long-term implications and ethical considerations, and advancing understanding of generative AI's societal effects.

Keywords: agent-based model · prediction · Artificial Intelligence · generative AI · social and economic prediction

1 Introduction

Generative artificial intelligence (AI) systems have gained significant traction in recent years [21], revolutionizing various industries such as healthcare, finance, and entertainment. These systems can autonomously generate content, including text, images, audio, and video, mimicking human-like creativity. While generative AI holds immense promise in enhancing [22] productivity and innovation, its widespread adoption raises concerns about its potential social and economic consequences. Therefore, there is a pressing need to understand and predict the implications of generative AI within societal frameworks.

In this paper, we aim to explore the social and economic consequences of using generative AI through the lens of agent-based modeling (ABM). Our objectives include proposing a possible agent-based model to simulate the impact of generative AI adoption and its interactions within socio-economic systems. Specifically, we seek to:

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- Conduct a comprehensive literature review to identify existing research on generative AI's social and economic implications.
- Propose an agent-based model that captures the complex dynamics of generative AI adoption and its effects on various societal factors.
- Implement the proposed model and validate its efficacy in predicting the social and economic consequences of using generative AI.
- Present the results of our simulations and analyze the potential implications for policy-making and decision-making processes.

Our approach begins with a thorough literature review to gather insights into generative AI's social and economic impacts. Building on existing research, we propose an agent-based model that incorporates key variables and relationships relevant to adopting and utilizing generative AI within society. We then implement the model using appropriate simulation techniques and validate its performance against real-world data where possible. Finally, we present the results of our simulations, highlighting key findings and discussing their implications for stakeholders and policymakers.

Our study aims to contribute to a better understanding of the complex interactions between generative AI and socio-economic systems, providing valuable insights into the potential consequences of its widespread adoption. Through agent-based modeling, we seek to offer a predictive framework for assessing the social and economic implications of using generative AI, thereby informing decision-making processes and facilitating the development of policies that balance innovation with societal well-being.

2 Literature Review

Agent-based modeling (ABM) emerges as a robust methodology for predicting the multifaceted impact of generative artificial Intelligence (AI) on socio-economic systems [1, 2]. This innovative approach facilitates the simulation of micro-level agents whose interactions give rise to macroscopic patterns aligned with predetermined objectives, providing insights into the intricate dynamics inherent in generative AI systems [2, 3]. By reverse-engineering desired outcomes, researchers can unravel the underlying rules and parameters governing these agents, thereby enhancing our understanding of AI's societal implications [2].

Furthermore, ABM holds promise for evaluating the social repercussions of generative AI systems across diverse modalities, including text, images, audio, and video [4, 5]. By specifying fundamental agent-rule components and permissible combinators, ABM enables a nuanced analysis of various dimensions such as biases, stereotypes, representational harms, cultural values, and disparate performance [5]. Additionally, ABM facilitates the assessment of financial costs, environmental impacts, and labor costs associated with data and content moderation, contributing to a comprehensive understanding of AI's socio-economic ramifications [5].

Leveraging insights from ABM empowers researchers to make informed decisions regarding integrating generative AI into societal frameworks [6, 7]. Comprehensive simulations and analyses, supported by empirical evidence, enable stakeholders to anticipate and address complex challenges posed by AI technologies, thereby maximizing societal benefits while mitigating potential negative consequences [6, 7].

In conclusion, ABM is a valuable tool for forecasting and analyzing generative AI systems' social and economic impacts [8]. By simulating complex interactions and dynamics, ABM facilitates a comprehensive understanding of AI's potential societal consequences, informing strategic decision-making and policy development [9].

3 Proposing a Set of Agents

In our agent-based model, we aim to predict the impact of Generative AI adoption on various societal factors such as education, skills, employment, and government regulation. The model incorporates three primary types of agents: individual agents, business agents, and government agents. The dynamics of each agent are described by differential equations representing their continuous-time evolution. This model is based on design science research [19] and follows similar architecture to previous multi agent systems studies [20].

3.1 A. Individual Agents

The dynamics for individual agents involving education and skill acquisition follow logistic growth models and differential equations commonly used in educational and psychological studies [10]. The sigmoid function used for modeling skill acquisition represents the concept of diminishing returns, a principle well-documented in both educational theory and cognitive psychology [11, 12]. Each agent seeks education (E(t)) and acquires skills (S(t)). Education is influenced by the rate of seeking (α), and skills are influenced by education and the learning rate (β). The equations governing individual agents are:

$$dE/dt = \alpha \cdot (1 - E(t)) \tag{1}$$

$$dSdt = \beta \cdot E(t)S(t) = 11 + e - \beta \cdot E(t), normaliz : bw\ 0\ and\ 1$$

Applying a sigmoid function to the skill level as it's updated introduces a non-linear growth pattern. Early on, as education increases, skills will grow quickly. As skills approach the maximum limit (asymptote of the sigmoid function), additional education results in smaller increases in skill, reflecting a more realistic learning curve. Practical Implications:

- It represents a realistic learning curve where initial education leads to significant skill gains, but these gains taper off as one becomes more skilled.
- It models the psychological principle of diminishing returns in learning.
- It can simulate scenarios where individuals continue to learn and develop skills, but the impact of further education is less pronounced as they become more skilled.

3.2 B. Business Agents

Business agents' behavior, particularly their adoption of generative AI based on available skills, can be modeled by logistic growth influenced by internal learning rates, echoing theories from business management and economics regarding technology adoption [13]. Businesses adopt Generative AI (A(t)) based on the skills possessed by individual agents. The adoption rate is influenced by the learning rate of businesses (γ).

The equation governing business agents is:

$$dA/dt = \gamma \cdot (1 - A(t)) \cdot S(t) \tag{2}$$

3.3 C. Labor Market (Employment):

The integration of skills' probability density functions into labor market dynamics uses statistical methods typical in labor economics, especially for modeling labor supply and demand shifts due to technological change [14]. Let f(S, t) represent the skills' probability density function (PDF) at time t, where S is the skill level. The total supply of labor (Total Supply Labor(t)) is given by the integral of the product of skill level and probability density function:

$$Total\ Supply\ Labor(t) = \int[-\infty, \infty]\, S \cdot f(S,\ t) \cdot dS \tag{3}$$

The total demand factor (Total Demand Factor(t)) is influenced by the adoption of Generative AI (A(t)) and other potential factors:

$$Total\ Demand\ Factor(t) = \gamma \cdot (1 - A(t)) \tag{4}$$

The dynamics of employment are governed by the rate of change of the integral representing the minimum of total supply labor, total demand factor, and the maximum supply labor threshold (Max Supply Labor):

$$dEmployment/dt = d/dt[min(\int[-\infty, \infty]S \cdot f(S,\ t) \cdot dS,\ \gamma \cdot (1 - A(t)),\ Max\ Supply\ Labor)] \tag{5}$$

3.4 D. Government Agent

The modeling of government regulation as a response to AI adoption levels can draw on theories from regulatory economics and public policy, particularly those discussing the feedback mechanisms between industry behavior and regulatory adjustments [15]. The government regulates AI development (R(t)) based on the level of Generative AI adoption. The regulation rate is influenced by a regulation factor (δ). The equation governing the government agent is:

$$dR/dt = \delta \cdot (A(t) - R(t)) \tag{6}$$

3.5 E. Model Dynamics and Predictions

Education and Skills: Individual agents continuously seek education, leading to an increase in skills over time. This reflects the ongoing learning and skill development in the population.

Generative AI Adoption: Businesses adopt Generative AI at a rate influenced by the population's skills. As skills increase, the adoption of AI by businesses is expected to grow.

Employment: Employment is a dynamic variable influenced by both the supply and demand for labor. The model predicts how the adoption of Generative AI impacts the balance between labor supply and demand, affecting overall employment levels.

Government Regulation: The government regulates AI development based on the level of AI adoption. This regulation is a feedback mechanism that aims to control and manage the societal impact of AI.

Differential equations and integrals allow for a continuous-time representation of agent behaviors and their interactions, providing insights into the long-term effects of Generative AI adoption on various societal aspects..

4 Implementation

We have implemented the proposed agent-based model using the Python programming language, leveraging libraries such as NumPy and Matplotlib to facilitate its development. The model architecture revolves around four main classes:

- IndividualAgent: Represents individual agents engaged in seeking education and supplying labor.
- BusinessAgent: Reflects businesses adopting generative AI technology and influencing economic labor demand.
- LaborMarket: Facilitates the matching of labor supply and demand, serving as the dynamic nexus of the labor ecosystem.
- GovernmentAgent: Governs the regulation of AI development based on prevailing AI adoption levels, shaping the technological landscape.

Upon initialization, the model is equipped with parameters such as learning rates, adoption rates, and regulatory factors. We establish initial conditions for education, skills, AI adoption, and regulation before commencing simulation over multiple time steps, enabling observation of its behavior and prediction of outcomes. Figure 1 shows a small agent community simulation.

The simulation outcomes provide invaluable insights into generative AI adoption's potential social and economic ramifications. Notable trends include businesses' escalating adoption of AI as individuals acquire skills, thereby influencing employment levels and government regulation. The model is a versatile tool for exploring diverse scenarios and conducting thorough analyses of parameter impacts on outcomes.

From a software engineering perspective, our code adheres to best practices in design and implementation. Embracing an object-oriented paradigm, we organize functionality into cohesive classes—IndividualAgent, BusinessAgent, LaborMarket, GovernmentAgent, and AgentBasedModel—enhancing readability and modularity. This architectural approach promotes scalability and maintainability by encapsulating related behavior and attributes within well-defined abstractions.

Each class's constructor methods (init) are central in initializing object attributes and fostering encapsulation and abstraction. This design decision facilitates code reusability and clarity by encapsulating object state and behavior within self-contained units. The simulate method within the AgentBasedModel class encapsulates the simulation logic, ensuring separation of concerns and modularity. This modular structure allows for seamless modification, extension, or replacement of simulation components without disrupting other model facets.

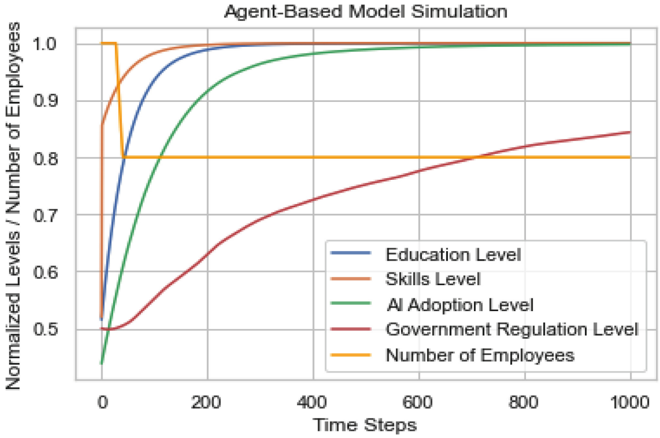

Fig. 1. Small Agent-Based Model Simulation**.**

Moreover, the set_initial_conditions method empowers users to specify initial parameters and conditions, augmenting simulation flexibility and configurability. By decoupling initialization logic from the primary simulation loop, this method facilitates experimentation with diverse scenarios and parameter values, bolstering sensitivity analysis and model validation efforts.

Random variability in alpha, beta, and gamma parameters imbues the simulation with stochasticity, mirroring real-world uncertainties and heterogeneities. This stochastic element enriches the model's realism, enabling the exploration of probabilistic outcomes and scenarios.

Furthermore, error-handling mechanisms are implemented to safeguard against negative values or invalid states in specific attributes, such as demand_factor and regulation. These defensive programming practices fortify simulation stability and correctness, ensuring robustness and reliability in results.

In summary, our agent-based model epitomizes rigorous software engineering principles and design patterns, harnessing the versatility of Python and the robust capabilities of libraries like NumPy and Matplotlib. It offers a flexible, robust, and interpretable framework for in-depth analysis of labor market dynamics, facilitating comprehensive studies at the intersection of economics, education, and technology adoption.

5 Results and Discussion

The model presented may give some insights into education level, skills level, AI adoption, government regulation, and employment level. This is shown in Fig. 2 (next page) where we use a large community (100 k) of agents over 100 simulations and 1k timesteps.

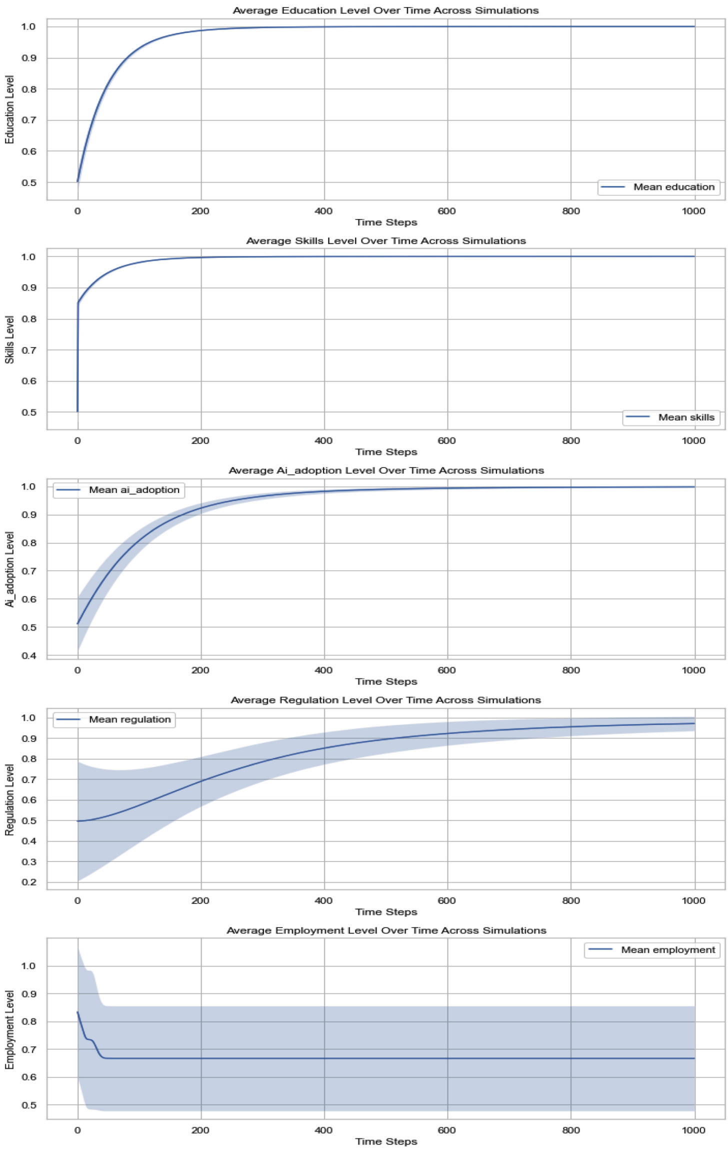

Fig. 2. Agent-Based Model Simulation.

The education level shows a logistic growth pattern, quickly reaching a saturation point. This reflects a scenario where individuals rapidly acquire education until a certain threshold, beyond which additional education does not significantly increase the education level. This could imply diminishing returns to investment in education or that other factors may limit further growth once a certain education level is reached. Which is consistent to current literature [16].

The skills level derived from education using a normalized sigmoid function also follows a logistic growth curve but with a different scale. This shows that as individuals become more educated, their skills increase at a diminishing rate, approaching an upper limit. This could reflect real-life scenarios where, after a certain point, further education results in smaller incremental increases in practical skills.

AI Adoption: The level of AI adoption grows over time, suggesting that businesses continuously adopt more AI technology as they respond to the skills available in the labor market, like in [18]. The availability of skilled labor, government regulations, and the businesses' internal decision-making processes could influence the adoption rate.

The regulation level appears to be increasing steadily. This could be a government's response to the rising adoption of AI, aiming to manage the impact on the labor market and society. The model suggests a lag or a gradual approach to regulation, which may be due to bureaucratic inertia or a deliberate phased approach to implementing regulations.

The employment level initially decreases, which could be due to AI adoption's impact on the labor demand [17]. However, it stabilizes and does not drop below a certain threshold, possibly due to the employment threshold parameter that prevents employment from falling too low. This could represent social safety nets or policies that maintain a minimum level of employment regardless of technological impact.

In practical terms, these trends could inform policymakers about the importance of:

- Ensuring that education leads to the acquisition of relevant skills in demand in an AI-driven economy.
- Monitoring the impact of AI on employment and being ready to intervene with policies to support those displaced by technology.
- Planning for a future where AI is more prevalent and ensuring that regulations are adaptive and responsive to the pace of technological change.
- Supporting continuous learning and skill development to maintain employability in a changing labor market.

6 Conclusions

This paper describes an agent-based model (ABM) to predict the social and economic consequences of using generative artificial Intelligence (AI). Through simulations conducted using the proposed model, we have explored the potential impacts of generative AI adoption on various societal factors, including education, employment, and government regulation. Our simulations have provided insights into the dynamics of generative AI adoption and its interactions within socio-economic systems. We have observed trends such as the increasing adoption of AI by businesses as the population's skills improve and the potential implications for employment levels and government regulation. Key Findings:

- Education and Skills Development: The simulation revealed a logistic growth in education and skills levels, pointing towards a saturation point beyond which additional education does not proportionally enhance skills. This suggests the need for optimizing educational resources and strategies to maximize effective learning and skill acquisition without unnecessary overextension.
- AI Adoption Trends: AI adoption was observed to increase steadily, influenced by the availability of skilled labor and regulatory frameworks. This underscores the importance of aligning educational outcomes with market needs, ensuring that the labor force is equipped to handle and benefit from emerging AI technologies.
- Regulatory Dynamics: The gradual increase in regulatory measures in response to AI adoption highlights the necessity for governments to adopt a proactive and phased approach to regulation. This strategy allows for the accommodation of technological advancements while ensuring that societal impacts are managed and mitigated.
- Employment Impact: The initial decline followed by stabilization in employment levels indicates the disruptive impact of AI on traditional jobs, countered by employment policies possibly designed to uphold a minimum level of workforce engagement. This aspect of the findings stresses the importance of having robust social safety nets and policies that can adapt to technological disruptions.

Based on the findings of this study, we recommend the following actions for stakeholders:

- Educational Policy Reform: Policymakers should focus on revising educational curricula to emphasize skills that are directly relevant to an AI-driven economy. This involves not only technical skills related to AI and data science but also adaptive skills such as problem-solving, critical thinking, and lifelong learning capabilities.
- Strategic AI Integration: Businesses should strategically adopt AI technologies, with a focus on augmenting rather than replacing human labor where possible. Investment in employee training to work alongside AI will be crucial for maximizing productivity and innovation.
- Proactive Regulatory Frameworks: Governments should develop flexible, forward-looking regulatory frameworks that can quickly adapt to new developments in AI technology. This involves regular dialogue with technologists, business leaders, and academics to anticipate future trends and potential impacts.
- Support for Displaced Workers: There is a pressing need for policies that support workers displaced by AI, such as retraining programs, unemployment benefits, and career counseling services. These programs should be designed to quickly and effectively re-integrate workers into the evolving job market.
- Lifelong Learning Systems: The development of continuous education and training systems is essential. These systems should be accessible to all workers throughout their careers, allowing them to continuously update their skills and stay relevant in a rapidly changing economic landscape.

However, it is essential to note that our model relies on certain assumptions and parameter values that may not fully capture the complexity of real-world scenarios. In future work, there is a need to refine and validate the model by estimating parameters based on real-life statistics and data. We can enhance the model's predictive accuracy and reliability by calibrating the model to fit empirical observations better.

Additionally, future research could explore the long-term implications of generative AI adoption, considering technological advancements, societal attitudes, and regulatory changes. Furthermore, there is a need to assess the potential ethical and moral implications of using generative AI, including bias, privacy, and accountability issues. Our study represents an initial step toward understanding and predicting generative AI's social and economic consequences. Refining and expanding our model in future research can further advance our understanding of this rapidly evolving technology and its impact on society.

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