Reimagining Economic Theory in the Age of Machine Learning and Big Data

Journal of Development Economics and Management Research Studies (JDMS)
A Peer-Reviewed Open Access International Journal
ISSN: 2582 5119 (Online)
Crossref Prefix No: 10.53422
13 (29), 01 - 10, July – September, 2026
@Center for Development Economics Studies (CDES)
Reprints and permissions
https://www.cdes.org.in/
https://www.cdes.org.in/about-journal/

REIMAGINING ECONOMIC THEORY IN THE AGE OF MACHINE LEARNING AND BIG DATA

T. Lakshmi Pradha[1] and S. Thirunavukkarasu[2]

Abstract

The rapid expansion of digital technologies and the growing availability of large-scale data are transforming the way economies operate and how economic questions are studied. As economies become increasingly data-driven, Machine Learning (ML) and Big Data are providing economists with new ways to understand, model, and predict economic behaviour. This chapter explores how these technologies are reshaping economic theory by complementing traditional approaches with more dynamic, predictive, and evidence-based methods. It traces the evolution of economic thought from classical and neoclassical perspectives to modern computational approaches, highlighting the need to move beyond conventional assumption-based models in an increasingly complex digital economy. The chapter also explains the roles of Artificial Intelligence (AI), Machine Learning, Deep Learning (DL), Natural Language Processing (NLP), and Large Language Models (LLMs), and examines their applications across sectors such as finance, e-commerce, healthcare, agriculture, governance, and education, with a particular focus on India's digital transformation. Rather than replacing established economic theories, these technologies strengthen them by enabling real-time analysis, more accurate forecasting, deeper behavioural insights, and better-informed policy decisions. While challenges related to data privacy, cybersecurity, algorithmic bias, and ethical governance remain, the article argues that integrating computational intelligence with established economic principles is essential

[1] Assistant Professor and HOD, Department of MBA, Guru Nanak College, Velachery, Chennai-600 0042.

[2] President, Centre for Development Economics Studies and Former Principal and HoD of Economics, Ramakrishna Mission Vivekananda College (Autonomous), Chennai, India. **https://orcid.org/0000-0001-7803-7274**

for building more adaptive, inclusive, and empirically grounded economic frameworks for the digital age.

Keywords: Artificial Intelligence (AI); Machine Learning (ML); Big Data Analytics; Deep Learning (DL); Large Language Models (LLMs); Natural Language Processing (NLP); Economic Theory; Digital Economy; Computational Economics; India.

Introduction

Economic theory uses assumptions to simplify complex and intricate real-world problems or situations into manageable models with precise predictive power and a scientific system. It is like a foundational principle that serves as a ‘filter’ to isolate specific variables and study their interaction with simultaneous factors. Traditionally, it relied on core categories encompassing psychological or behavioural, structural, institutional and market assumptions. The conventional economic theories integrate assumptions of rational agents, equilibrium conditions, representative behaviour, etc., for achieving a coherent, analytically strong, structured framework classified as classical, neoclassical and modern frameworks of thought.

The classical work of Leon Walras (1874) and the general equilibrium models of Arrow and Debreu (1954) suggested that markets naturally move toward equilibrium states that allocate resources efficiently. The neoclassical school was subsequently emboldened by rational choice theory (Becker, 1976) and utility maximisation (Samuelson, 1947), and Samuelson (1947) reinforced this foundation with mathematical rigour in economic analysis, making equilibrium a central organising principle in modern economic thought. Simon’s (1955) theory of ‘bounded rationality' analyses decision-making that is constrained by cognitive limits and imperfect information. It is deepened by the more realistic behavioural assumptions propounded by Kahneman and Tversky (1979) in their ‘prospect theory’. In the recent development of ‘computational and agent-based approaches’ of Tesfatsion and Judd (2006), the scope of economic analysis was further expanded.

The description of the economic models has replaced the single representative agent with multiple, heterogeneous agents whose interactions give rise to complex macroeconomic patterns, smearing the analytical simplicity of equilibrium-based reasoning to a richer, data-driven understanding of adaptive, non-linear, and heterogeneous economic systems. The real-world economies are more dynamic, highly diverse, and shaped by complex interdependencies. With the increase in high-frequency and large-scale datasets and advances in computational tools, economists are forced to apply machine learning and data-intensive methods for empirical analysis and for developing theories. Machine Learning (ML) and Big Data have become transformative tools widely applied in the refinement of theoretical models, the testing of complex hypotheses, and also for the discovery of new relationships.

These technologies extend the tradition of formal modelling by enabling economists to process high-dimensional data, uncover complex non-linear relationships, and simulate dynamic systems beyond the reach of traditional analytical tools (Varian, 2014). ML techniques, such as neural networks, decision trees, and reinforcement learning models, enable adaptive prediction and pattern discovery without imposing restrictive parametric forms (Athey, 2018). According to Sendhil Mullainathan and Jann Spices (2017), Machine Learning (ML) tools help predict outcomes using large datasets. They look similar to econometrics but serve a different purpose. ML focuses on prediction, while economics frequently focuses on estimating relationships. Economists can use ML when prediction is useful, but they must understand how these tools work to avoid using them incorrectly. Making the ideas behind ML clearer helps ensure it is used appropriately and adds value to economic analysis.

ML is phenomenal at predicting outcomes, but economists want to understand and identify causal relationships. That is where traditional tools like instrumental variables, regression discontinuity, and difference-in-difference remain essential—they help uncover real causal effects and evaluate whether a policy or program actually works.

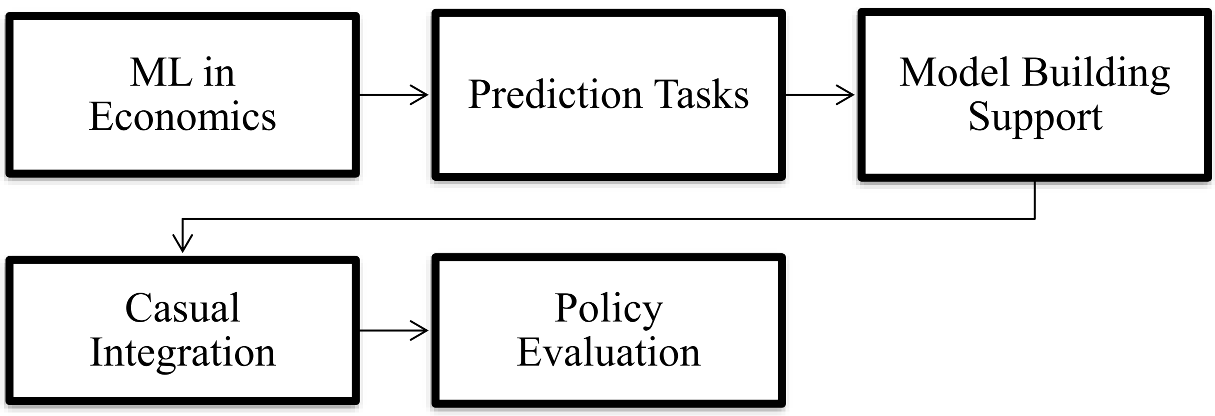
ML can still play a significant supporting role, especially when dealing with big datasets or improving the accuracy of certain steps in analysis. However, to use it better, economists need to comprehend both what ML is good at and where it falls short. When used thoughtfully, ML can complement, but it cannot replace, traditional econometric methods. It helps and strengthens them in several ways:

1. ML is useful for better prediction by handling large, complex datasets and uncovering patterns to make more accurate forecasts of economic events.
2. ML helps to identify and select variables from among the many exploratory factors that matter most. This improves the economic model specification and reduces the risk of including irrelevant or confusing variables.
3. ML methods help to detect nonlinear patterns and interactions automatically for building richer and more realistic economic models.
4. ML is significant for understanding heterogeneous effects. It can divulge how government policies or programs impact different groups differently. This makes economic models more comprehensive and useful for policy design.
5. ML improves causal models and can enhance causal-inference methods by improving control variable selection, estimating treatment effects more flexibly, or analysing big administrative datasets.
6. ML technique helps to create simulation and agent-based models with realistic behavioural rules by facilitating economists to model complex systems like financial markets, supply chains, etc., more accurately. Computational modelling opened new frontiers for economists to build theory using Agent-Based Models (ABMs), Dynamic Stochastic General Equilibrium (DSGE) simulations, and Heterogeneous-Agent Frameworks (HANK) to simulate economies populated by diverse, interacting agents. This will go beyond equilibrium analysis, enabling the exploration of emergent behaviour such as bubbles, contagion, innovation diffusion, and inequality dynamics. In addition, high-performance computing is useful for simulating transactions to test theoretical mechanisms that are analytically intractable.

7. A synthesis of mathematical reasoning and algorithmic simulation in ML, while synthesising data and computation, is presented in the following sequences:
    - ❖ From Equilibrium to Dynamics, where the focus has shifted from static equilibria to adaptive, evolving systems.
    - ❖ From Representative to Heterogeneous Agents, where the economic models now incorporate diverse preferences, constraints, and expectations.
    - ❖ From Closed-Form to Simulated Solutions, where numerical experiments are gaining theoretical legitimacy alongside analytical proofs.
8. From Deterministic to Probabilistic Frameworks, where ML introduces probabilistic modelling that captures uncertainty more realistically. The Challenges and Ethical Considerations in the data-driven theory enhance realism. As a result, economists must integrate computational innovation with ethical responsibility and theoretical clarity, which face new challenges:
    - ➢ Interpretability: Machine learning models can be opaque, complicating theoretical interpretation.
    - ➢ Bias and Fairness: Big Data may replicate existing social and structural inequalities.
    - ➢ Epistemic Boundaries: A balance must be struck between empirical prediction and causal explanation rooted in theory.

Currently, Big Data has expanded the empirical foundations of economic inquiry by providing granular, real-time observations of individual and institutional behaviour (Einav & Levin, 2014). Parenthetically, when it is integrated with computational simulations and agent-based modelling (Tesfatsion & Judd, 2006), these methods facilitate the study of emergent phenomena, viz., network effects, contagion, and market instability, that are fundamental for understanding complex economic systems. The adoption of computational and data-driven methodologies represents not a departure from theoretical economics, but an evolution toward empirically enriched, behaviourally grounded, and computationally rigorous frameworks that enhance the explanatory and predictive capacity of modern economic theory.

The following flow chart illustrates how Machine Learning is used in building economic models:



Flow chart 1: Machine Learning in building economic models

Flow Chart 1 demonstrates how Machine Learning (ML) chains the development of economic models by converting large volumes of raw data into meaningful insights. The process begins with collecting and preparing data, followed by selecting relevant variables and training ML algorithms to identify hidden patterns, relationships, and behavioural trends within these large and complex datasets. The models are then tested and refined before being applied to forecasting, policy evaluation, and economic decision-making. Unlike traditional economic models, which often depend on fixed assumptions, ML models continuously improve as new data become available, making them more accurate, flexible, and responsive to changing economic conditions. As a result, machine learning enables economists to build more reliable, data-driven models that better reflect the complexities of modern economies and support more effective policy and business decisions.

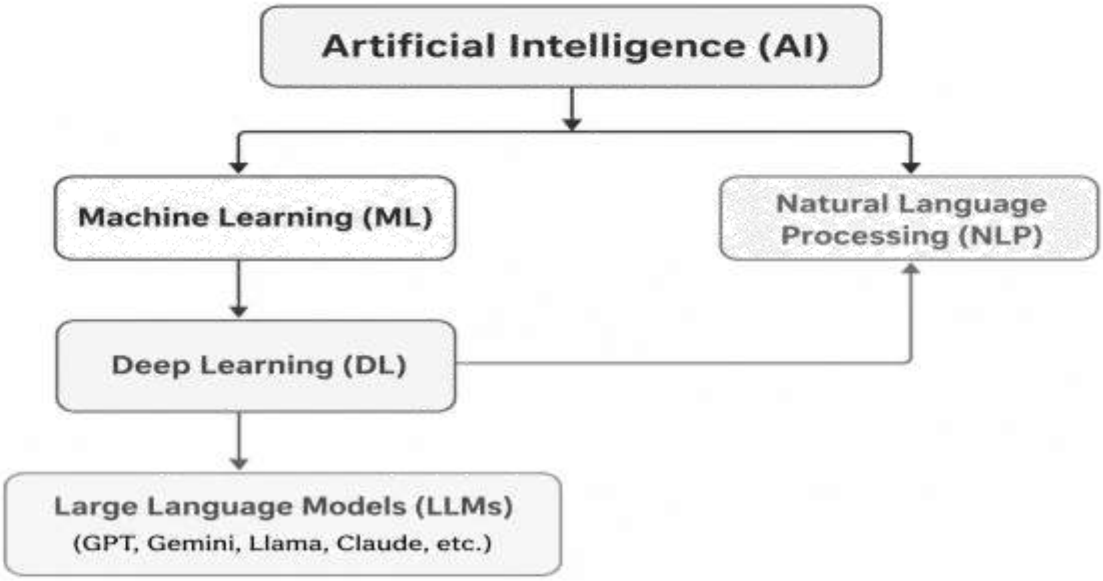


Figure 2. Hierarchical Relationship among Artificial Intelligence (AI), Machine Learning (ML), Deep Learning (DL), Natural Language Processing (NLP), and Large Language Models (LLMs).

Figure 2 portrays the hierarchical evolution of artificial intelligence technologies and their relevance to contemporary economic research. Artificial Intelligence (AI) forms the overarching discipline encompassing computational methods that emulate human intelligence. Artificial Intelligence (AI) provides the broad technological foundation, with Machine Learning (ML) and Natural Language Processing (NLP) emerging as two of its most influential branches for data-driven economic research.

Machine Learning (ML) enables computers to learn from large volumes of data, uncover hidden patterns, and make predictions, allowing economists to complement traditional theory with evidence-based insights. Machine learning also facilitates economists to test theories against real-world data with greater accuracy and at a much larger scale.

Deep Learning (DL), a more advanced form of machine learning, can model complex and nonlinear economic relationships, improving forecasting accuracy, behavioural analysis, and policy evaluation.

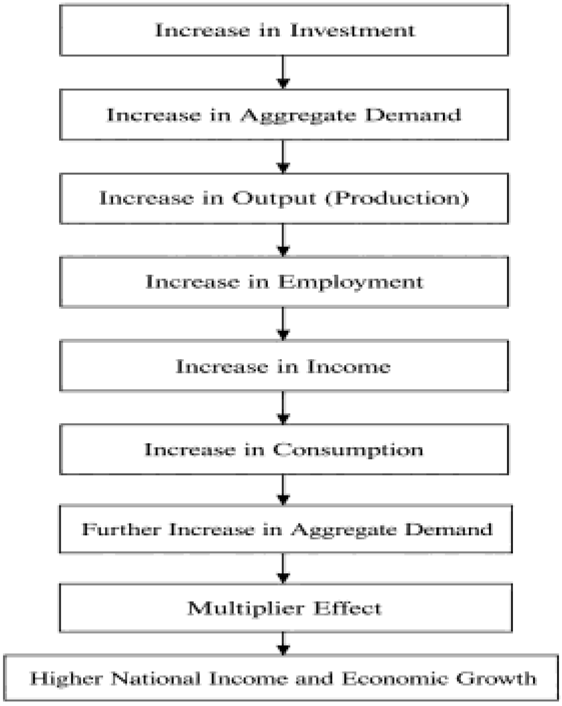
Large Language Models (LLMs) build on deep learning to understand and generate human language, making it possible to analyse vast collections of economic texts such as policy documents, financial reports, academic literature, and academic literature, thereby enriching empirical research and supporting more informed policy decisions.

Together with Big Data, these technologies are reshaping economics by moving beyond purely assumption-driven models towards more data-informed, predictive, and adaptive approaches, paving the way for a new generation of economic theory better suited to the complexities of the digital economy.

The figure illustrates that from Artificial Intelligence (AI) to Machine Learning (ML), Deep Learning (DL), NLP, and LLMs—reflects the rapid evolution of analytical tools available to economists. Rather than replacing classical economic theories, these technologies build upon and strengthen them by providing richer data, more powerful analytical methods, and improved predictive capabilities. They support the development of more adaptive, evidence-based, and empirically grounded economic theories that are better equipped to address the challenges of today's data-driven digital economy.

It is appropriate to apply Keynes' Chain of Causation, which provides a useful starting point for understanding how economic activity unfolds. In the traditional Keynesian framework, investment stimulates aggregate demand, leading to higher output, employment, income, and consumption, ultimately driving economic growth. Today, advances in machine learning and big data strengthen this framework by enabling economists to analyse economic behaviour using vast amounts of real-time data. These technologies improve demand forecasting, reveal complex relationships that conventional models may overlook, and provide deeper insights into consumer behaviour and policy outcomes. Rather than replacing Keynesian economics, they enhance its explanatory and predictive power, making economic analysis more responsive to the realities of a rapidly evolving digital economy.

Keynes' Chain of Causation



The Keynesian Chain of Causation deliver a massive economic domino effect. It says that when businesses start spending, that initial spark ripples through the whole system—creating jobs, boosting incomes, and proving that consumer demand, rather than just factory supply, is what really runs the engine. If we look at this classic idea through the lens of "Reimagining Economic Theory in the Age of Machine Learning and Big Data," those dominoes don't just fall faster and the entire game board changes.

Key Applications & Impact

In e-commerce and retail, they enable personalised shopping experiences, accurate demand forecasting, and efficient supply chain management. In finance, they strengthen credit assessment, fraud detection, risk management, and financial inclusion. Healthcare is benefiting from improved diagnostics, personalised treatment, and better resource allocation, while agriculture is becoming more productive through precision farming, crop forecasting, and climate-resilient decision-making. Beyond these sectors, ML and BD are helping governments design evidence-based policies, improve public service delivery, and strengthen digital governance, while the education sector is using adaptive learning technologies to create more personalised and effective learning experiences.

E-commerce and Retail: Machine learning and big data have transformed retail by enabling personalised customer experiences, intelligent product recommendations, dynamic pricing, demand forecasting, and supply chain optimisation. These developments challenge traditional assumptions of homogeneous consumer behaviour and provide economists with richer insights into market dynamics and consumer decision-making.

Finance: AI-driven analytics are redefining financial markets through improved risk assessment, fraud detection, algorithmic trading, credit scoring, and customer relationship management. These capabilities support more accurate modelling of financial behaviour and contribute to more robust theories of market efficiency, risk, and decision-making under uncertainty.

Healthcare: The integration of machine learning into healthcare improves disease diagnosis, personalised treatment planning, and resource allocation. From an economic perspective, these innovations enhance productivity, reduce healthcare costs, and strengthen evidence-based approaches to health economics and public policy.

Agriculture: By analysing data on weather, soil conditions, crop performance, and resource use, AI enables farmers to make more informed decisions. This supports sustainable agricultural practices, improves productivity, and contributes to more resilient models of agricultural and environmental economics.

Governance and Public Services: Governments increasingly use big data and AI to design evidence-based policies, improve public service delivery, optimise resource allocation, and develop smart cities. These advances encourage a shift from reactive policy-making to predictive and adaptive governance, enriching public economics and policy analysis.

Education (EdTech): AI-powered learning platforms offer personalised learning pathways and adaptive educational experiences based on individual needs and performance. This not only enhances learning outcomes but also provides new insights into human capital development, labour market readiness, and the economics of education.

These applications demonstrate how machine learning, big data, and AI are transforming the way economic activities are analysed, predicted, and managed. By generating real-time, data-driven insights across diverse sectors, they enable economists to move beyond static, assumption-based models towards more dynamic, adaptive, and evidence-based theories. This shift lies at the heart of reimagining economic theory in the age of machine learning and big data, where computational intelligence complements traditional economic principles to better explain and address the complexities of the digital economy.

This part of the paper brings out the connection between the traditional and modern approaches towards economic modelling in the midst of data transformation using advanced technologies.

Data Value Chain Framework: A modern understanding towards economic modelling

The Data Value Chain explains how raw data becomes economic value:

1. Data Generation (transactions, sensors, digital platforms)
2. Data Storage (cloud infrastructure)
3. Data Processing (big data systems)

4. Analytics & Machine Learning

5. Decision & Monetisation

Economic value is created at stages 4 and 5, where machine learning transforms data into a competitive advantage.

In this changing environment, Machine Learning (ML) and Big Data are playing an increasingly important role in driving economic growth, improving productivity, and fostering innovation. By turning vast amounts of data into meaningful insights, these technologies help businesses and policymakers make faster, smarter, and more informed decisions. Their influence is visible across almost every sector of the economy.

These developments are transforming the way economists understand and analyse economic behaviour by moving beyond traditional assumption-based models towards more dynamic, data-driven, and predictive approaches. At the same time, the growing use of these technologies raises important challenges related to data privacy, cybersecurity, algorithmic bias, and regulatory oversight, making ethical and inclusive digital governance essential. Against this backdrop, this study explores how Machine Learning and Big Data are reshaping a country's economy and contributing to the reimagining of economic theory in the era of big data and intelligent analytics.

Conclusion

The convergence of Machine Learning, Big Data, and Computational Methods marks one of the most profound transformations in economic thought. These tools not only refine classical theories but also enable new paradigms grounded in complexity, heterogeneity, and empirical depth. The future of economic theory will rest on the synergy between computation and conceptualisation—combining the analytical rigour of traditional economics with the exploratory power of modern data science.

The rise of Machine Learning (ML) and Big Data is transforming the way economists understand and analyse economic systems. Rather than relying solely on traditional models built on simplifying assumptions, economists can now use real-time, data-driven insights to better explain consumer behaviour, market trends, and policy outcomes. Across sectors such as finance, healthcare, agriculture, retail, governance, and education, these technologies are improving efficiency, fostering innovation, and supporting more informed decision-making. For India, this digital transformation presents significant opportunities to accelerate economic growth, strengthen public policy, and promote inclusive development. At the same time, concerns surrounding data privacy, cybersecurity, algorithmic bias, and ethical governance must be carefully addressed to ensure that technological progress benefits society as a whole. Ultimately, machine learning and big data are not replacing established economic theories; rather, they are enriching them with powerful analytical capabilities that make economic research more dynamic, evidence-based, and responsive to the complexities of the digital age. Reimagining economic theory, therefore, means integrating traditional economic principles with computational intelligence to build a more adaptive and forward-looking discipline.

Reference:

1. Aghion, P., Jones, B. F., & Jones, C. I. (2019). *Artificial intelligence and economic growth* (NBER Working Paper No. 23928). National Bureau of Economic Research.
2. Arrow, K. J., & Debreu, G. (1954). Existence of an equilibrium for a competitive economy. *Econometrica, 22*(3), 265–290. **https://doi.org/10.2307/1907353**
3. Athey, S. (2019). The impact of machine learning on economics. In A. Agrawal, J. Gans, & A. Goldfarb (Eds.), *The economics of artificial intelligence: An agenda* (pp. 507–552). University of Chicago Press.
4. Becker, G. S. (1976). *The economic approach to human behaviour*. University of Chicago Press.
5. Chen, H., Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly, 36*(4), 1165–1188.
6. Esteva, A., Kuprel, B., Novoa, R. A., Ko, J., Swetter, S. M., Blau, H. M., & Thrun, S. (2017). Dermatologist-level classification of skin cancer with deep neural networks. *Nature, 542*(7639), 115–118. **https://doi.org/10.1038/nature21056**
7. Farmer, J. D., & Foley, D. (2009). The economy needs agent-based modelling. *Nature, 460*(7256), 685–686. **https://doi.org/10.1038/460685a**
8. International Data Corporation. (2022). *Worldwide Global DataSphere forecast*. IDC.
9. Janssen, M., & Kuk, G. (2016). Big and open linked data (BOLD) in government: A challenge to transparency and privacy? *Government Information Quarterly, 33*(4), 363–368.
10. Kahneman, D., & Tversky, A. (1979). Prospect theory: An analysis of decision under risk. *Econometrica, 47*(2), 263–291. **https://doi.org/10.2307/1914185**
11. Khandani, A. E., Kim, A. J., & Lo, A. W. (2010). Consumer credit-risk models via machine-learning algorithms. *Journal of Banking & Finance, 34*(11), 2767–2787.
12. Mayer-Schönberger, V., & Cukier, K. (2013). *Big data: A revolution that will transform how we live, work, and think*. Houghton Mifflin Harcourt.
13. Mitchell, T. M. (1997). *Machine learning*. McGraw-Hill.
14. Mullainathan, S., & Spiess, J. (2017). Machine learning: An applied econometric approach. *Journal of Economic Perspectives, 31*(2), 87–106. **https://doi.org/10.1257/jep.31.2.87**
15. Samuelson, P. A. (1947). *Foundations of economic analysis*. Harvard University Press.
16. Simon, H. A. (1955). A behavioural model of rational choice. *The Quarterly Journal of Economics, 69*(1), 99–118. **https://doi.org/10.2307/1884852**
17. Tesfatsion, L., & Judd, K. L. (Eds.). (2006). *Handbook of computational economics: Vol. 2. Agent-based computational economics*. Elsevier.
18. Varian, H. R. (2014). Big data: New tricks for econometrics. *Journal of Economic Perspectives, 28*(2), 3–28. **https://doi.org/10.1257/jep.28.2.3**
19. Walras, L. (1874). *Éléments d'économie politique pure*. L. Corbaz.

***