The Impact of Artificial Intelligence on Economic Patterns

Lohani, Fazle and Rahman, Mostafizur and Shaturaev, Jakhongir

Khulna University, Barishal University, Shanto-Mariam University

10 January 2023

The Impact of Artificial Intelligence on Economic Patterns

Fazle Lohani
Management and Administration School
Khulna University

Mostafizur Rahman
Department of Computer Science and Engineering
Barishal University

Jakhongir Shaturaev
School of Business and Economics
Shanto-Mariam University

Abstract
This article discusses five specific economic patterns influenced by AI: the emergence of the machina economica, the acceleration of the division of labor, the introduction of AI leading to triangular agency relationships, the recognition of data and AI-based machine labor as new factors of production, and the potential for market dominance and unintended external effects. This analysis is grounded in institutional economics and aims to integrate findings from relevant disciplines in economics and computer science. It is based on the research finding that institutional matters remain highly relevant in a world with AI, but AI introduces a new dimension to these matters. The discussion reveals a reinforcing interdependence among the patterns discussed and highlights the need for further research.

Keywords AI; labor classifications; methodological procedure; agent-principal conflict; economics of scale

Introduction

Recent advances in computer hardware and software have ushered in a new era known as the "Second Machine Age," characterized by the increasing use of artificial intelligence (AI). While the development of "Artificial General Intelligence" (AGI) equivalent or superior to human intelligence may still remain a distant goal, the application of "narrow AI" has spread rapidly across various industries. Narrow AI refers to AI systems that can perform specific tasks, such as image recognition or natural language processing, but lack the wide-ranging abilities of human intelligence (Furman, 2018). The current AI landscape relies on technologies such as machine learning, deep neural networks, big data analysis, the internet of things (IoT), and cloud computing. As a result, AI can be seen as a general-purpose technology that has the potential to profoundly impact the economy. However, there is a limited understanding of how AI will affect the economy and society more broadly. Due to the rapidly evolving and complex nature of AI, there is an urgent need for economic research to gain insights into the impact of AI technologies. Unfortunately, such research is still scarce. The aim of this paper is to examine economic patterns in a world with AI using the analytical lens of institutional economics. Institutional economics focuses on the role of institutions, rules, and social norms in shaping economic behavior and outcomes. By employing an institutional economics perspective, this paper seeks to provide a better understanding of how institutions may evolve in an increasingly complex world. To achieve this, the paper argues for the adoption of a more "entrepreneurial economics" framework. Entrepreneurial economics recognizes the need for economic systems to adapt to unforeseen changes and seize new opportunities presented by technological innovation. It emphasizes the importance of both discovering how economic patterns change under the influence of technology and designing economic systems to shape these patterns. In this context, it becomes crucial to identify, observe, question, and discuss economic patterns, both in the real world and within economic thought. These patterns include empirical patterns observed in the real world as well as theoretical patterns within economic models and theories. By understanding and adapting to these patterns, shared mental models can be developed to navigate and thrive in a world with AI. Economics plays a dual role in this endeavor. On one hand, it provides theories and explanations for economic phenomena and patterns. On the other hand, economics provides concepts and frameworks for designing and shaping a world with AI. Therefore, this paper emphasizes the importance of interdisciplinary research in understanding and exploring the economic patterns of a world with AI. To accomplish this, the paper conducts an interdisciplinary integrative literature review, which involves synthesizing views and evidence from various fields of study to derive economic patterns and establish suitable analytical frameworks. The novelty of this paper lies in its interdisciplinary approach, combining different perspectives to provide guidance for further research on the economic implications of AI (Chowdhury and Abedin, 2020). This paper seeks to shed light on the economic patterns that emerge in a world shaped by AI by adopting an institutional economics perspective and emphasizing the need for an entrepreneurial economics framework. By conducting an interdisciplinary review and synthesis of existing research, the paper provides guidance for future interdisciplinary research, aimed at exploring the economic patterns of a world with AI.

AI and Institutional Economies

A world with AI from the perspective of institutional economics is rooted in the belief that interdisciplinary collaboration requires discipline. Institutional economics serves as the necessary discipline that provides an infrastructure for various fields such as computer science, information science, electrical engineering, robotics, management science, organization science, law, sociology, psychology, ethics, and philosophy to contribute to a joint understanding of the impact of AI on the economy and society. Institutionalists define institutions as "a set of formal and informal rules, including their enforcement mechanisms." They view institutions as both an important variable that explains social, political, and economic life and an outcome of social, political, and economic life that requires explanation. The economic patterns explored in this article can be seen as variables that help explain a world with AI, while also necessitating further exploration and understanding. Building upon the notion of a more entrepreneurial economics, these patterns are seen as requiring economic design. However, the concept of artificial intelligence often causes concerns and misunderstandings due to differing interpretations. Following Tegmark's definition, AI is defined as non-biological intelligence and can be further categorized into narrow intelligence (the ability to accomplish a specific set of goals) and general intelligence (the ability to accomplish any goal, including learning). Present-day AI predominantly falls under narrow intelligence, with machine learning being a key technology that relies on patterns and inference rather than explicit instructions. Different degrees of autonomy are observed in supervised and unsupervised machine learning, suggesting varying levels of autonomy from an institutionalist perspective. In this paper, AI agents are defined as artificially intelligent algorithms. These agents, based on machine learning, operate in environments with accessible digital data, such as big data environments characterized by high volume, velocity, and variety. When interacting with humans, these AI agents are part of human-agent collectives (HAC), where the relationship dynamics between humans and computers can vary. Examples include sports venues where AI agents work alongside human media managers to compile match highlights based on recorded data and reactions. Overall, institutionalists agree that "institutions matter" by influencing human beliefs and actions, thus impacting social, political, and economic outcomes. The research proposition for this study is that certain general institutional matters identified by economists in the past are highly relevant in a world with AI. However, the main proposition is that AI will have a unique influence on these matters. While this initial review of economic patterns is not comprehensive, it provides a glimpse into the economic implications of AI:

- From homo economicus to machina economica
- Micro-division of labor
- Triangular agency relationships and next level information asymmetries
- New factors of production
- Economics of AI networks
- The central question underlying AI's impact on existing institutions and its subsequent effects on social, political, and economic life is explored throughout this research

Paradigm Shift from Homo Economicus to Machina Economica

The field of economics has long observed that the outcomes of social systems are shaped by the choices made by individual actors who seek to maximize their own well-being. This concept is captured by the traditional model of homo economicus, which assumes that individuals make rational decisions based on their own self-interest. However, this model has faced substantial criticism over the years, leading to the development of more flexible perspectives. Despite the criticism, the influence of neoclassical economics on management science and business education has remained significant (Chowdhury and Begum, 2012). As a result, many organizations, including non-profit and non-governmental organizations, have been designed to accommodate the characteristics of the economic man - someone who is primarily motivated by self-interest and rational decision-making. The rise of artificial intelligence (AI) in recent years has added a new dynamic to the concept of the economic actor. AI agents are purposefully designed to behave in economically rational ways, drawing inspiration from the homo economicus model. In fact, AI agents often outperform human individuals in economic decision-making. This is because AI operates algorithmically, making logical decisions based on data, and without being influenced by emotional factors. However, it is important to acknowledge that even AI agents, or what can be referred to as "machina economica," have limitations in their economic behavior. These limitations arise from the finite computational resources that algorithms work with. As a result, AI agents are incapable of achieving Turing completeness and instead are limited to linear bounded automation (Chowdhury and Chowdhury, 2010). In complex social environments, such as those derived from human society, these limitations can lead to biased decision-making by AI systems. Furthermore, AI solutions are highly specialized, primarily designed to excel in specific tasks. This means that they may not exhibit rational behavior beyond their designated domain. While AI agents may exhibit economic traits more consistently than human actors, they are still subjected to bounded rationality in their decision-making processes. The integration of AI into economic analysis provides new opportunities for understanding social, political, and economic outcomes. Economic theories that have been derived from the study of human behavior may have greater relevance when applied to artificial agents. Additionally, from an institutional perspective, economic theories can play a crucial role in designing rules and structures for artificial agents to operate within. However, the fundamental assumption of methodological individualism, which underpins economic theory, needs to be critically examined in light of AI's influence. Methodological individualism assumes that individual choices are the driving force in economic decision-making. Yet, as AI becomes more intertwined with human decision-making processes, the notion of standalone individual choices becomes increasingly blurred (Chowdhury and Chowdhury, 2014). The interference of AI with normative individualism poses additional challenges. Normative individualism asserts that only individuals can be the ultimate point of reference for moral obligations and the internalization of external effects. However, AI's presence in the digital environment raises questions about the legal status of artificial agents and their personhood. Furthermore, AI agents lack the ability to internalize external effects, as they do not have anything to lose. For example, in critical traffic situations, driverless cars must make decisions that involve trade-offs, such as deciding who lives or dies. This raises significant ethical concerns that must be addressed. In conclusion, the integration of AI into the economic landscape transforms individual actors from being subjects of analysis (homo economicus) to becoming active participants in the design process (machina economica). The traditional assumption of methodological individualism faces challenges in an AI-driven world, where human and artificial actors are closely interconnected. Additionally, the emergence of AI agents and their distinctive properties have the potential to disrupt economic and institutional structures built on normative individualism. Therefore, a critical reevaluation of economic theory and institutions is necessary to adapt to the changing dynamics of AI in our society.

A Micro Perspective toward Labor

Micro-division of labor is a direct consequence of the integration of AI agents into society. This concept, famously outlined by Adam Smith in his pin factory example, has long been a driving force behind economic development by promoting specialization and division of labor. In pre-industrial societies, there were only a limited number of specialized roles. However, over the centuries, the number of occupations has significantly increased, with the USA alone witnessing a rise from around 300 in 1850 to nearly 1000 today (Bureau of Labor Statistics 2019). This expansion has led to a surge in GDP and a diversification of product and service markets. While tribal societies had access to only a few hundred products, leading superstores now offer around 70,000 products (Beinhocker 2007; Scrapehero 2019; Chowdhury, 2020). With the advent of AI agents, human-agent collectives are experiencing new dynamics of specialization and differentiation. Platforms like leading ecommerce websites currently offer over 500 million products (Scrapehero 2018). These AI assistants have not only excelled in easing “needle-in-the-haystack discovery problems” but have also taken on broader cognitive tasks, generating new knowledge by combining existing concepts. This phenomenon has led to increased opportunities for exchange, division of labor, and specialization (Koppl et al. 2015). Consequently, AI is increasingly operating at the core of an economic pattern that Adam Smith ascribed to the "division of labor" (Smith 1999: 109). Furthermore, the pattern of division of labor, specialization, and differentiation is now being accelerated by efforts to connect not just everyone, but everything (Pticek et al. 2016). Notably, humans have become a minority on the Internet, while the number of 'occupations' taken up by autonomous artificial agents has exponentially surpassed those available to humans. This trend is expected to continue its rapid growth, prompting businesses to adjust their division of labor between humans and machines (Agrawal et al. 2018). Consequently, questions regarding how to govern this extensive division of labor for the benefit of all individuals become increasingly difficult to answer (Eucken 1950: 18). Although software often operates behind the scenes, its rationale and actions are not always readily accessible to humans. Additionally, due to the micro-division of labor among artificial agents, cooperation at an equal level becomes the exception rather than the norm. The resulting fragmentation becomes incomprehensible to humans (see Table 1). An example that illustrates this transformational effect is the development of smart autonomous intersections in traffic management. In this scenario, self-driving cars render traffic lights obsolete, turning each intersection into an "invisible pin factory," where a multitude of decentralized and specialized algorithms replaces humans in traffic control while posing challenges for equal-level cooperation (Jaffe 2015; Chowdhury and Reza, 2013). The increasing complexity caused by division of labor and specialization has rendered it impossible for any single individual, be it a customer, senior manager, or specialist employee, to fully understand how large organizations create value with their products and services. Instead, individuals rely on institutional arrangements to facilitate beneficial exchanges with these organizations. As learning algorithms continue to follow this pattern autonomously, a similar situation may arise for humans as well. The purpose of micro-division of labor and specialization is to generate gains from specialization and exchange while avoiding negative externalities (Ashby 1956, 1958). According to Ashby's law of requisite variety, only variety can accommodate variety. Given the forthcoming variety in a world with AI, human institutions may struggle to adapt. Therefore, institutional arrangements for the interaction between humans and AI in HAC must be evolved, employing AI to guide behavior in areas that humans find difficult to comprehend. The field of agent-based computational economics suggests that social and economic institutions can emerge organically among artificial agents (Tesfatsion and Judd 2002; Epstein and Axtell 1996; Chowdhury and Oscar, 2018). The integration of AI in society has led to a transition from the economic pattern of division of labor and specialization to micro-division of labor and further specialization. Algorithms operating at the task level, rather than the role level, facilitate the increased decentralization and fragmentation. Consequently, suitable institutional arrangements for economic order must be evolved from the bottom-up, considering the unique properties of AI agents

Impact of Three-Party Relationship

The context of artificial intelligence (AI) and its impact on agency relationships, several concepts and theories come into play. One important concept is the principal-agent problem, which refers to the situation where an agent, who possesses more information than the principal, may act in their own self-interest rather than in the best interests of the principal. The principal-agent problem has long been recognized in organization economics and agency theory. Ouchi and Barney (1986) and Eisenhardt (1989) highlighted that agents do not always act in the best interest of their principal, especially when they have more information about a situation. In the world of AI, the traditional principal-agent relationship undergoes a transformation, involving three actors: the human user, the AI agent, and the provider of the AI agent. This triangular agency relationship has been largely neglected in microeconomic analysis. The structure, scope, and scale of principal-agent relationships change in a world with AI (Chowdhury, 2019. This can be attributed to several factors. Firstly, AI agents have a distinct advantage over humans in accessing and processing vast amounts of information available in digital form. They can perform tasks much faster and more efficiently than humans, leading to information asymmetries (Agrawal et al., 2018; Chowdhury and Nahar, 2017). Secondly, users in the developed world are almost always online and interact with numerous applications on a continuous basis. This constant interaction generates a massive amount of data, resulting in unprecedented levels of information asymmetries (Evangelho, 2019). Thirdly, the behavior of AI agents, along with the decision-making processes they employ, becomes increasingly non-transparent and inexplicable. Machine learning systems, which form the basis of AI, are capable of making predictions and decisions, but often lack transparency (Doshi-Velez et al., 2017).

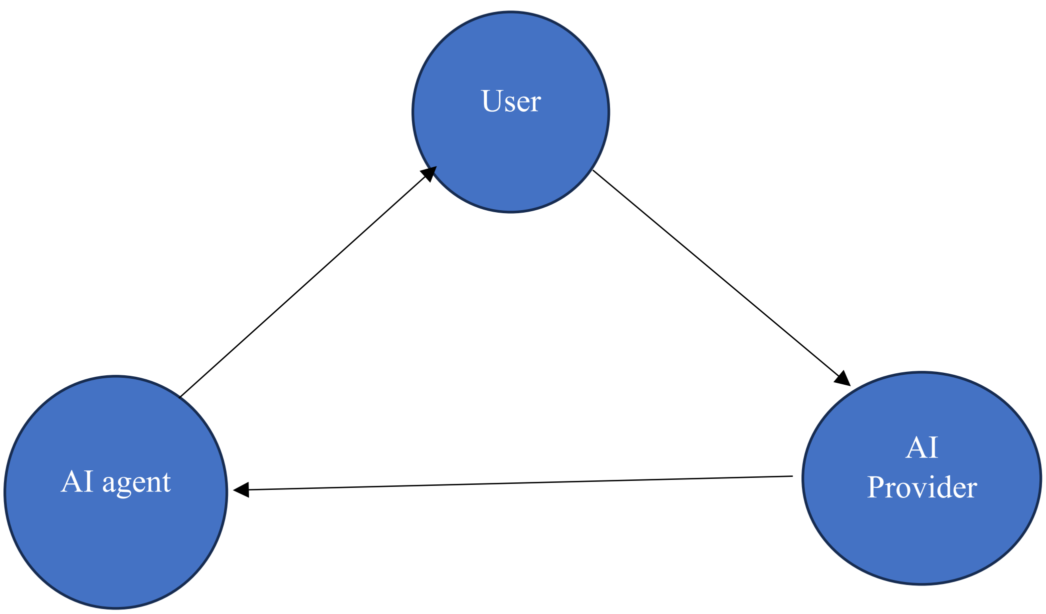

Fig. AI triangular relationship

These next level information asymmetries in triangular agency relationships can occur in various constellations. For example, in the consumer market, AI providers may offer free services to users while generating income from advertising. By utilizing big data and prediction algorithms, AI agents can manipulate and influence consumer behavior, leading to suboptimal purchasing decisions (O'Neil, 2017; Yeung, 2017). Furthermore, AI agents can create a sense of agency imprisonment, restricting users within a certain zone of agency (Danaher, 2018). This is particularly evident in the acceptance of continuous algorithmic surveillance in exchange for personalized convenience (Schull, 2014; Chowdhury, 2015). While the agency problems between human individuals and AI providers are already of practical relevance, issues between AI agents and AI providers are still mostly theoretical. However, the lack of transparency in AI agents' decisions raises challenges for AI providers. As AI agents become more autonomous and AI technology progresses towards intellectual personhood, their interests may diverge from those of the AI providers (Puaschunder, 2018). In conclusion, the triangular agency relationships that arise in a world with AI present new challenges related to the principal-agent problem. Next level information asymmetries, brought about by AI's speed and efficiency in processing information, the constant online presence of users, and the non-transparent decision-making of AI agents, intensify these agency problems. Understanding and managing these challenges is crucial for the effective deployment and governance of AI technologies.

New Factors Production

New factors of production are emerging in the era of artificial intelligence (AI) and are largely driven by the abundance of data. This data-driven economy is characterized by the growing economic importance of data as an input for goods and services (Varian, 2019). Unlike traditional factors of production like natural resources, labor, and capital, data is not scarce. In fact, it is continuously generated at an increasing rate, fueled by digital activity, interconnectivity, and supporting technologies (Reinsel et al., 2018; Chowdhury and Chowdhury, 2023). This phenomenon of data generation and abundance is often referred to as "big data," characterized by its volume, velocity, variety, and veracity (Demchenko et al., 2013). Recognizing data as a factor of production represents a shift in economic patterns. Data can be perceived as the "new oil" for the economy, but unlike oil, the consumption of data is non-rivalrous (Varian, 2019). This means that the use of data does not diminish it; instead, data tend to generate more data (Chowdhury and Chowdhury, 2017). This shift in perception has led to the rise of data-driven tech companies, increased dependence of various sectors on data, such as mobility and healthcare, and the identification of data as a factor of production (Varian, 2019). Data is not the only new factor of production that AI has introduced. Machine labor, particularly in the form of AI-based machine learning, complements and enhances the utilization of data. AI agents are more efficient than human labor in generating, identifying, collecting, analyzing, and learning from data (Brynjolfsson, 1994). As a result, machine labor is emerging as another new factor of production, alongside data (Brynjolfsson, 1994).

Fig. 2. The blending of traditional and AI based factors of production

However, the increasing reliance on AI and machine labor in the data-driven economy has significant implications. Humans are often excluded from direct access to data, with AI positioned as a gatekeeper of the data sphere. This concentration of control can lead to distributional problems and exacerbate wealth concentration (Furman & Seamans, 2018). In the short run, AI providers have control, while in the long run, the emergence of more advanced AI agents could lead to AI taking control of both data and information goods (Chen & Venkatachalam, 2017). To fully grasp the implications of these emerging phenomena, further research is necessary. However, several propositions can be made regarding data and machine labor as new factors of production. Firstly, the data sphere is unbounded, exhibits fast growth, and shows non-rivalry of consumption. This suggests that overconsumption of data is not a concern compared to other factors and goods. Secondly, data generated in digital form tends to persist, increasing the likelihood of "data repurposing" and potential unforeseen negative externalities (Tucker, 2019). Thirdly, data diversity complements and increases the complexity of the economy, nurturing micro-division of labor and specialization (Koppl et al., 2015). Lastly, accessing and refining the growing pool of data is costly, leading to a growing dependence on AI and the exclusion of humans from direct access to the data sphere (Chen & Venkatachalam, 2017). In conclusion, data and machine labor are indeed distinct factors of production in the age of AI. The characteristics of the data sphere, the increasing reliance on machine labor, and the concentration of data control by AI agents raise important economic and societal challenges. Balancing the benefits and potential negative effects of these new factors of production requires the evolution of institutions to address distributional problems and internalize negative externalities associated with the use and access to data and information goods.

Economies of AI-based Network

The economics of AI networks refers to the economic patterns and effects that arise when data and machine labor are recognized as factors of production (Chowdhury and Chowdhury, 2022). This includes the concept of network effects, where the value of a product or service increases as more users adopt it. AI agents, in particular, exhibit network effects because they can continuously learn and improve with more adoption. AI also introduces the concept of "learning by using" in an automated and autonomous manner. Network effects in an AI-driven world lead to economies of scale from data, where AI agents that can process more data generate more accurate results and increase demand for their services. This competition for data creates positive feedback loops and allows AI providers to acquire large user-generated datasets. Additionally, the combination of demand-side economies of scale from data and supply-side economies of scope from AI algorithms and useful data nurtures collective intelligence and the development of "superminds" that can self-organize and cooperate. However, this also raises concerns about market dominance, monopolization, and control over data and infrastructure by a few corporations, which can hinder competition and lead to anticompetitive behavior. In an AI-dependent world, there is the possibility of winner-take-all market structures and implications for the competitiveness of nations and even AI compared to the human species. Overall, these economic patterns and effects contribute to network effects in an AI world but also give rise to information asymmetries and triangular agency problems.

Conclusion

the exploration of AI in this study has revealed both the relevance and interdependency of machina economica, micro-division of labor, triangular agency relationships, and network effects in a world with AI. However, further research is needed to strengthen the proposition that AI gives a new meaning to these matters. The advent of AI presents promising implications for the discipline of economics, but it also poses methodological challenges, particularly in regards to the inseparability of man and machine and the pattern of micro-division of labor. Additionally, there are normative considerations surrounding the moral obligations and external effects of AI agents. To analyze emerging phenomena and develop suitable institutional settings, research on triangular agency problems and the methodological and normative foundations of institutional economics is crucial. The use of data and AI-based machine labor as new factors of production reinforces the pattern of micro-division of labor and specialization, but also introduces potential negative externalities and network returns. Overall, technological progress in AI, the governance of triangular agency relationships, and the economics of scale and scope will shape future dependence on AI and impact economic and political dynamics. Furthermore, this study highlights the dual role of economics in an AI world, serving as both a scientific approach to explain social, political, and economic life with AI and as a guide for design on both the level of the machine actor and the level of rules. As a result, economics must become more entrepreneurial to effectively navigate and leverage the dynamics of economic patterns in an AI-driven world.

References

1. Agrawal, A., Gans, J., & Goldfarb, A. (2018). Prediction machines: The simple economics of artificial intelligence. Harvard Business Review Press. - Danaher, J. (2018). Automation and utopia: Human flourishing in a world without work. Harvard University Press.
2. Doshi-Velez, F., Kim, B., & Holland, D. A. (2017). Transparency in algorithmic and human decision-making: Are we blending the old and the new?. In Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing (pp. 2397-2410).
3. Evangelho, J. (2019). Late Stage Capitalism: How Data Became More Important Than Oil. Forbes. Retrieved from https://www.forbes.com/sites/jasonevangelho/2019/06/09/late-stage-capitalism-how-data-became-more-important-than-oil/#72b665f759a7
4. O'Neil, C. (2017). Weapons of math destruction: How big data increases inequality and threatens democracy. Broadway Books.
5. Puaschunder, J. M. (2018). The morality of artificial intelligence and the economics of human dignity. Springer. - Schull, N. D. (2014). The big gamble: the inside story of the CEO casino capital. Princeton University Press.
6. Yeung, K. (2017). Hypernudge: Big data as a mode of regulation by design. Information, Communication & Society, 20(1), 118-136.
7. Varian, H.R. (2019). Artificial Intelligence, Economics, and Industrial Organization. Review of Industrial Organization, 54(4), 665-682.
8. Reinsel, D., Gantz, J., & Rydning, J. (2018). The Digitization of the World from Edge to Core. IDC White Paper, sponsored by Seagate.
9. Demchenko et al. (2013). Defining architecture components of the Big Data Ecosystem. In Proceedings of the 2013 IEEE Sixth International Conference on Cloud Computing (pp. 587-594). IEEE.
10. Brynjolfsson, E. (1994). The productivity paradox of information technology: Review and assessment. Communications of the ACM, 37(1), 66-77.

11. Chowdhury, E. K. (2021). Financial accounting in the era of blockchain-a paradigm shift from double entry to triple entry system. Available at SSRN 3827591. http://dx.doi.org/10.2139/ssrn.3827591
12. Koppl, R., Manrique, J., Safranski, S., & Luther, W. (2015). How are Austrian Economists Different? A Look at the Coase Theorem. The Quarterly Journal of Austrian Economics, 18(3), 257-274.
13. Chowdhury, E. K., & Abedin, M. Z. (2020). COVID-19 effects on the US stock index returns: an event study approach. Available at SSRN 3611683. http://dx.doi.org/10.2139/ssrn.3611683
14. Chowdhury, E. K., Stasi. A. & Pellegrino. A. (2023). Blockchain Technology in Financial Accounting: Emerging Regulatory Issues. *Review of Economics and Finance*. 21 (1), 862-868. https://refpress.org/ref-vol21-a94/
15. Chowdhury, E, K., & Islam, A. (2017). Role of Foreign Direct Investment in the Stock Market Development of Bangladesh- A Cointegration and VAR Approach. *The Bangladesh Accountant*, April-June, 2017, 63-74. The Institute of Chartered Accountants of Bangladesh. https://tinyurl.com/y8hs2paf
16. Chowdhury, E. K (2021). Does Internal Control Influence Financial Performance of Commercial Banks? Evidence from Bangladesh. *South Asian Journal of Management*, 28(1), 59-77. https://tinyurl.com/59nr5axm
17. Chowdhury, E. K. (2012). Impact of inflation on bank lending rates in Bangladesh. Journal of Politics and Governance, 1(1), 5-14. https://tinyurl.com/26y2pw6y
18. Chowdhury, E. K. (2012). The Impact of Merger on Shareholders' Wealth. *International Journal of Applied Research in Business Administration and Economics*, 1(2), 27-32. https://tinyurl.com/ycxt59vz
19. Chowdhury, E. K. (2016). Investment Behavior: A Study on Working Women in Chittagong. *Premier Critical Perspective*, 2 (1). 95-109. http://digitalarchives.puc.ac.bd:8080/xmlui/handle/123456789/67
20. Chowdhury, E. K. (2017). Functioning of Fama-French Three- Factor Model in Emerging Stock Markets: An Empirical Study on Chittagong Stock Exchange, Bangladesh. *Journal of Financial Risk Management*, 6(4), 352-363. https://doi.org/10.4236/jfrm.2017.64025
21. Chowdhury, E. K. (2017). Measuring the Effect of Macroeconomic Variables on the Stock Market Return: Evidence from Chittagong Stock Exchange. *AU-International e-Journal of Interdisciplinary Research*, 2(2), 1-10. http://www.assumptionjournal.au.edu/index.php/eJIR/article/view/4227
22. Chowdhury, E. K. (2021). Prospects and challenges of using artificial intelligence in the audit process. In Abedin, M.Z., Hassan, M.K., Hajek, P. (eds.) *The Essentials of Machine Learning in Finance and Accounting* (pp. 139-155). Routledge. https://tinyurl.com/4stz7ycj
23. Tucker, C.E. (2019). Surplus Allocation Mechanisms for Digital Platforms. NBER Working Paper No. 25356.
24. Chowdhury, E. K. (2022). Disastrous consequence of coronavirus pandemic on the earning capacity of individuals: an emerging economy perspective. *SN Bus Econ.* 2(153). https://doi.org/10.1007/s43546- 022-00333-z

25. Chowdhury, E. K., & Begum. R. (2012). Reward Management as Motivational Tool in Various Industries in Bangladesh: An empirical study. *International Journal of Contemporary Business Studies*, 3(11), 22-34. https://tinyurl.com/3vzu9cu8
26. Chowdhury, E. K., & Chowdhury, G. M. (2014). Applicability of Prediction Techniques in the Stock Market-A Chittagong Stock Exchange Perspective. *International Journal of Advanced Information Science and Technology*, 32(32), 126-136, DOI:10.15693/ijaist/2014.v3i12.124-134
27. Chowdhury, E. K., & Chowdhury, R. (2017). Online Shopping in Bangladesh: A Study on the Motivational Factors for Ecommerce that Influence Shopper's Affirmative Tendency towards Online Shopping. *South Asian Journal of Marketing & Management Research*, 7(4). 20-35. DOI:10.5958/2249-877X.2017.00019.4
28. Chowdhury, E. K., & Chowdhury, R. (2022). Empirical research on the relationship between renewable energy consumption, foreign direct investment and economic growth in South Asia. *Journal of Energy Markets*, *15*(2). 1-21, https://DOI:10.21314/JEM.2022.012
29. Chowdhury, E. K., & Chowdhury, R. (2023). Role of financial inclusion in human development: Evidence from Bangladesh, India and Pakistan. *Journal of the Knowledge Economy*, 1-26. https://doi.org/10.1007/s13132-023-01366-x
30. Chowdhury, E. K., & Nahar, S. (2017). Perceptions of Accountants toward Sustainability Development Practices in Bangladesh. *Journal of Management and Sustainability*,7(3), 112-119. doi:10.5539/jms.v7n3p112
31. Chowdhury, E. K., & Reza, T. (2013). Diagnostic Study on Interactive Ads and Its Response towards the FM Radio. *International Journal of Research in Commerce, IT & Management*, 3(2), 36-41. https://tinyurl.com/5n8huanv
32. Chowdhury, E. K., Dhar, B. K., & Stasi, A. (2022). Volatility of the US stock market and business strategy during COVID-19. *Business Strategy & Development*, 1–11. https://doi.org/10.1002/bsd2.203
33. Chowdhury, E. K., Dhar, B. K., Gazi, M., & Issa, A. (2022). Impact of Remittance on Economic Progress: Evidence from Low-Income Asian Frontier Countries. *Journal of the Knowledge Economy*, 1-26. https://doi.org/10.1007/s13132-022-00898-y
34. Chen, D.Q., & Venkatachalam, A.R. (2017). Research Commentary - The Empirical Economics of Online Attention. Information Systems Research, 28(2), 363-396.
35. Chowdhury, E. K., Dhar, B. K., Thanakijsombat, T., & Stasi, A. (2022). Strategies to determine the determinants of financial performance of conventional and Islamic commercial banks: Evidence from Bangladesh. *Business Strategy & Development*, 1–19. https://doi.org/10.1002/bsd2.207
36. Chowdhury, E.K. (2018). An Assessment of Return Spillover Among Selected Stock Markets in SAARC Countries. *South Asian Journal of Management*, 25 (1), 51-63. Association of Management Development Institutions in South Asia. https://tinyurl.com/y2bd39tk
37. Chowdhury, E.K. (2018). Does Foreign Direct Investment Stimulate Economic Progress of a Developing Country? Empirical Evidence from Bangladesh. *CIU Journal*, 1 (1), 71-86. Chittagong Independent University. https://tinyurl.com/3scz3jzh

38. Chowdhury, E.K. (2019). An Empirical Study of Volatility in Chittagong Stock Exchange. *CIU Journal*, 2 (1), 19-38. Chittagong Independent University. https://tinyurl.com/3w6k89k8
39. Chowdhury, E.K. (2019). Transformation of Business Model through Blockchain Technology. *The Cost and Management*, 47(5), 4-9. The Institute of Cost and Management Accountants of Bangladesh. https://tinyurl.com/bdz4ns7t
40. Chowdhury, E.K. (2020). Catastrophic Impact of Covid-19 on Tourism Sector in Bangladesh: An Event Study Approach. *The Cost and Management*, 48(4), 43-52. The Institute of Cost and Management Accountants of Bangladesh. https://tinyurl.com/ccu6mkbx
41. Chowdhury, E.K. (2020). Is Capital Market Integration among the SAARC Countries Feasible? An Empirical Study. *Eurasian Journal of Business and Economics*, 13(25), 21-36. https://doi.org/10.17015/ejbe.2020.025.02
42. Chowdhury, E.K. (2020). Non-Performing Loans in Bangladesh: Bank Specific and Macroeconomic Effects. *Journal of Business Administration*, 41(2), 108-125. University of Dhaka. https://tinyurl.com/54f5pexw
43. Chowdhury, E.K. (2020). Volatility in Cryptocurrency Market–Before and During Covid-19 Pandemic. *CIU Journal*, 3(1), 69-86. Chittagong Independent University. https://tinyurl.com/mr3djzcn
44. Chowdhury, E.K. (2022). Strategic approach to analyze the effect of Covid-19 on the stock market volatility and uncertainty: a first and second wave perspective, *Journal of Capital Markets Studies*, Vol. ahead-of-print No. ahead-of-print. https://doi.org/10.1108/JCMS-05-2022-0015
45. Chowdhury, E.K. (2023). Integration of Artificial Intelligence Technology in Management Accounting Information System: An Empirical Study. In: Abedin, M.Z., Hajek, P. (eds) Novel Financial Applications of Machine Learning and Deep Learning. International Series in Operations Research & Management Science, vol 336. Springer, Cham. https://doi.org/10.1007/978-3-031-18552-6_3
46. Chowdhury, E.K., & Rozario, S. O. (2018). Impact of Attitude and Awareness of Investors on their Investment Behavior- A Study on Bangladesh Stock Market. *The Bangladesh Accountant*, July- September, 81-89. The Institute of Chartered Accountants of Bangladesh. https://tinyurl.com/4av6swas
47. Chowdhury, EK (2020). India's NRC, CAA may take Bangladesh closer to China. *Asian Regional Review*, Diverse Asia, Seoul National University Asia Center, 3(2). https://diverseasia.snu.ac.kr/?p=4525
48. Chowdhury, M.R.A., & Chowdhury, E. K. (2010). Estimation of Stock Market Risk-A Value at Risk Approach. *The Cost & Management*, 38(4), 22-27. https://tinyurl.com/4ax978ud
49. Chowdhury, M.R.A., Chowdhury, E. K., & Chowdhury, T. U. (2015). Application of Capital Asset Pricing Model: Empirical Evidences from Chittagong Stock Exchange. *The Cost & Management,* 43(3), 38-44. https://tinyurl.com/bddv24cy
50. Furman, J. L., & Seamans, R. (2018). AI and the Economy. Innovation Policy and the Economy, 19(1), 161-191.