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DRIVERS OF CARBON EMISSIONS IN THE ERA OF ARTIFICIAL INTELLIGENCE: CASE OF JAPAN

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Abstract. This research is driven by the absence of a unified consensus regarding the relationship between artificial intelligence, energy consumption, and economic growth and their impact on CO_2 emissions. Not clear whether AI increases or decreases CO_2. The novelty – identification of the two-way causal link between the implementation of AI and carbon emissions, a dynamic not previously confirmed in the literature. The originality – the model tested on a scale of Japan as developed country which still around 90% depending on fossil fuels. Data period: 1995–2024. An ARDL-based econometric approach to analyze the long-term and short-term impacts and several diagnostics to improve the precision and reliability of the study results. Tests used: the Breusch-Godfrey Serial Correlation, Ramsey RESET, Breusch-Pagan-Godfrey, CUSUMSQ and CUSUM. The study outputs reveal that in Japan, AI and energy consumption are associated with an increase in carbon emissions, while exports – with decrease in emission levels. In developed economies governments recommended to lower CO_2 emissions by speeding up the shift toward renewable energy sources and investing in environmentally friendly AI technologies. Policymakers should adopt an integrated approach that links AI, energy, environmental, and economic policies, supported by regulatory reforms to promote sustainability and achieve carbon neutrality.

Keywords: Japan, artificial intelligence, economic development, energy use, carbon emissions, ARDL.

JEL Classification: O33, O40, Q43, Q55, F62, F64.

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1. Introduction

Over the past decade, artificial intelligence has assumed a progressively more significant role in fostering advancement across a wide range of industries. Nevertheless, the expanding adoption of artificial intelligence also exerts a substantial influence on energy demand and carbon emissions, giving rise to a multifaceted and interrelated dynamic that requires thorough and careful evaluation. While, as artificial intelligence systems expand, their greenhouse gas emissions raise concerns for today's generations (Tomlinson et al., 2024). In 2022–2023, the total carbon emissions level increased from 38,246.62 mt to 39,023.94 mt. This report shows the increase in total CO_2 from the preceding year to the current year (Crippa et al., 2023). Similarly, energy use per person increased from 21,154 kWh in 2022 to 21,394 kWh in 2023 (Our World in Data, n.d.). Both studies show increased indicators of energy use and CO_2 of recent years. Moreover, artificial intelligence tools can help detect gas leaks, monitor deforestation, and create environmentally sustainable materials. Constantinescu et al.

(2025) study reveals that technological factors are essential in shaping economic processes and international investment. However, the question remains: how much energy do AI tools actually consume, and do these costs outweigh or fall below their potential contribution to combating climate change? (De Bolle, 2024). So, we observe two versions of scientists. On the one hand, researchers argue that artificial intelligence significantly lowers CO_2. Conversely, in an analysis covering 74 countries, other scientists found that artificial intelligence has contributed to the escalation of global temperature rise, which not only did not reduce, but increased air pollution (Wang et al., 2024a). Thus, the development of information and communication technologies with the development of AI can have both an emission-increasing and a reduction effect, depending on the type of energy chosen (Kraujalienė et al., 2026). Hence, the environmental effects of artificial intelligence continue to be widely debated, with contrasting perspectives on whether its overall influence is predominantly detrimental or comparatively harmless.

Energy consumption, ecological balance, and environmental concerns are strongly interrelated within human activities. The growing levels of carbon emissions constitute a global challenge, primarily stemming from the energy requirements needed to sustain further economic progress in countries (Zhang et al., 2024a). Energy represents a crucial component of national development, as it supports domestic needs and commercial operations, while the expansion of these sectors is largely contingent upon the availability and intensity of energy supply (Pratiwi & Juerges, 2020). Industrialization and economic activity increase carbon emissions as energy demand grows, as does the use of fossil fuels (Kraujalienė et al., 2025). However, emissions from non-renewable energy sources and finite energy resources pollute the air, harm the environmental conditions, as well as affect people's well-being. These pollutants also damage water bodies and wetlands, threatening marine life (Kirikkaleli & Adebayo, 2021; Weili et al., 2022). In response to these challenges, achieving net-zero CO_2 emissions has become a central goal in the climate and energy policies of many countries worldwide (DeAngelo et al., 2021), Japan as well. This country is still around 90% uses fossil fuels for energy production, and is ranked in TOP5 world's largest oil consumer, the largest liquefied natural gas importer, and in TOP4 as the largest crude oil and coal importer (Adebayo et al., 2021; Tripathi et al., 2025), but also aiming to reach carbon neutrality by 2050 (Ohta & Barrett, 2023). In today's world, the demand for energy is rising due to population growth and urbanization (Osobajo et al., 2020). Nevertheless, the energy sector remains strongly dependent on low-cost options such as non-renewable energy sources, primarily for power generation, is contributing to the rise in atmospheric emissions, accelerating global warming, and intensifying other environmental challenges (Voumik et al., 2023).

The disparity between economic expansion and the rising volume of emissions has emerged as a major global concern. Economic development is frequently linked to elevated levels of CO_2 emissions (Zhang & Sharifi, 2024). For many countries, especially developing ones, driving economic development is a primary objective to improve living standards. However, as economic activities expand, energy demand rises, which consequently results in increased carbon dioxide emissions and contributes to environmental degradation (Khan et al., 2024). To address this, harmonizing economic expansion with CO_2 mitigation is necessary to maintain long-term environmental stability (Wang et al., 2022). In this context, Brock and Taylor maintain that sustainable economic development entails not only promoting economic expansion but also enhancing environmental conditions (Brock et al., 2005). Furthermore, from the nineteenth century, Reverend Thomas Malthus has been among the earliest thinkers to examine how economic processes influence environmental conditions (Glass, 1976).

In Figure 1 trend analysis of economic growth, AI, energy use and carbon emissions in Japan is presented in the period of 1995–2024. During last five years mentioned variables are more or less remain stable, except economic growth which is degreasing.

According to the World Bank, a number of different indicators are monitored, but some of the most important ones that describe the economic and environmental aspects are economic growth (measured by GDP), energy consumption and carbon footprint, assessed at the country level, regions or in other sections (Dong et al., 2018).

Some authors and a substantial number of studies have examined various models exploring the factors impacting environmental collisions. There are some variables affecting the population size and the per capita level for one citizen, and the degree of technological advancement as a part of economic progress. Energy use and economic determinants constitute major drivers of carbon emissions. At the initial stages of economic expansion, environmental conditions tend to deteriorate. The body of literature examining the relationship among economic growth, economic complexity, energy consumption, and environmental degradation is reviewed in order to determine the research gap (Afroz et al., 2024; Chen et al., 2016).

Some scientists have studied the cases of emerging economies (countries), their groups, e.g., BRICS (Brazil, Russia, India, China, South Africa). They examined the determinants of renewable energy sources and emissions, FDI (foreign direct investment), exports and the relationship between them. Authors mention that previous studies often did not examine this group of factors but rather examined these factors separately. Therefore, a broader model was needed that simultaneously addresses the impact of mentioned factors on countries

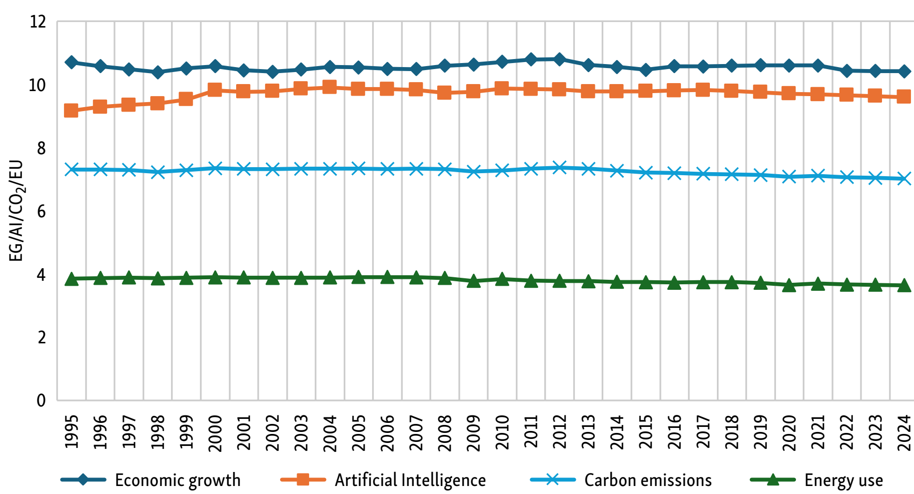

Figure 1. Trend evaluation of the research indicators in Japan over the period 1995–2024 (artificial intelligence, economic growth, energy use and carbon emissions) (prepared by authors, 2025)

(Iqbal et al., 2023; Zhang, 2021). Also, some researchers looked at how foreign-invested companies (FIEs) create carbon emissions through their exports. Using data from 59 countries between 2005 and 2016, the researchers found that about 40% of FIEs' emissions come from exported goods (Yan et al., 2023). Important to take into account, that export as a variable is influencing the country economics and sustainability results.

Thus, the main explanatory variables have been chosen as economic growth, energy use, and AI (as a huge user of energy consumption), when CO_2 playing the role of dependent variable, and export integrated as control variable. The determination of variables for the research is justified supported by literature review and research gaps explained below.

This research specifically focuses on Japan, a global leader in technology, to explore the interrelationships among AI, energy consumption, and CO_2. In the field of artificial intelligence development, Japan ranks among the world's leading countries, with the market size in the artificial intelligence sector projected to reach US$8.12 billion in 2024. The market is projected to expand at an annual growth rate of 28.48%, reaching US$36.52 billion by 2030. A recent survey found that 46.8% of businesses in Japan are using generative artificial intelligence. But Japan as developed country still relies on fossil fuels for energy production. Japan is among the top five largest oil consumers in the world., the biggest liquefied natural gas importer, in TOP4 largest crude oil importer, and in TOP3 largest coal importer, behind only China and India. Japan's fossil fuels account for about 90% of Japan's energy package, while oil represents a substantial share (40%) of its overall energy consumption. Despite the environmental concerns of coal, natural gas, fossil fuels, are becoming increasingly important energy sources. Their demand is growing as alternative energy sources to compensate for the lack of nuclear power (Adebayo et al., 2021; Tripathi et al., 2025). A new target of reaching net-zero carbon emissions by 2050 was announced in October 2020 by Japanese Prime Minister Yoshihide Suga, in April 2021, he announced an interim target of reducing emissions of 46% by 2030. Based on the election of US President Joe Biden in November 2020, who supported the need to reduce climate change, Suga supports and adopts the "Green Growth Strategy for Carbon Neutral by 2050". The report identifies 14 priority industries in various sectors that must achieve carbon neutrality by 2050. These include industries such as electricity, carbon recycling, nuclear, offshore wind, ammonium, hydrogen, fuel cell automobiles, logistics, shipping and aircraft, agriculture, ICT and semiconductors, materials recycling, etc. (Ohta & Barrett, 2023; Saqib et al., 2024). Hence, we see, that Japan is one of the biggest emitters in the world, but seeking to decarbonize the country which needs rapid energy transformation away from fossil fuels. Thus, the primary aim of this research is to examine the effects of AI, economic growth, energy consumption, and exports on CO_2 in Japan, a topic that has become highly significant. It sets this study apart is its exploration of both the long-term and short-term interactions among these indicators, as well as the inclusion of additional factors like exports in the period of 1995–2024. The results of the study offer a solid basis for developing policies that support the Japanese administration in reducing emissions while simultaneously encouraging the advancement of artificial intelligence. Policy recommendations may contribute to strengthening environmental sustainability not only in Japan but also worldwide (the Asia-Pacific region and South Asian Association for Regional Cooperation (SAARC)), particularly in other nations expanding their artificial intelligence industries.

This study helps expand existing knowledge by filling gaps in previous research in the following ways. The current scientific studies examine the environmental impact of various kinds of energy use, economic state, AI, and export factors, are based on environmental sustainability, carbon reduction, etc. However, only a limited number of studies explore the link between artificial intelligence and environmental sustainability. Thus, the research gaps found for this research are next: (1) From a scholarly standpoint, most existing research on the environmental sustainability of artificial intelligence primarily concentrates on carbon emissions. The influence of AI on energy consumption has received limited attention, and very few studies integrate multiple indicators within a single analysis. There is limited number of research works modelling the framework to analyse the impact of energy use, AI, and economic growth on CO_2 choosing exports as a control variable to ensure reliable results, by clarifying whether changes in emissions are due to differences in export levels. (2) In terms of the research object, the Chinese market has attracted the greatest research focus, whereas studies examining other countries have been relatively limited. (3) Moreover, AI as a variable in mentioned model was rarely used, especially evaluating developed countries, whose economic performance activities are still heavily dependent on traditional energy sources (non-renewable fuels). However, the country chosen for this study is a developed country – Japan, which is among the most industrially advanced economies globally, and still mostly using non-renewable energy sources.

This research is largely driven by the absence of a clear consensus regarding the exact links among energy consumption, artificial intelligence, economic growth, and CO_2 emissions on a scale of advanced economy.

This research is driven by the absence of a shared consensus regarding the exact relationship between AI and other variables as economic growth and energy use on CO_2 emissions within a developed country. Opinions of researchers differ on whether AI increases or decreases CO_2. The originality of this study stems from uncovering a two-way causal relationship between AI adoption and CO_2 emissions, a dynamic not previously confirmed in the literature. The originality – the model tested on a scale of Japan as developed country which still around 90% depending on fossil fuels.

By examining the relationship on how chosen factors interconnect, this research provides a valuable framework for future scholars to build upon. There are much research works prove that AI is excellent for optimization and efficiency increase, and it is right for emerging countries till they grow to developed and use much more energy. Accordingly, it also enhances a more comprehensive understanding of the wider environmental effects of artificial intelligence and energy consumption. The development of any country is closely tied to human activities, which require technology advancements that, in turn, depend on energy use. Artificial intelligence plays a transformative role in various sectors, making life easier and more efficient. Nevertheless, such development is associated with greater energy requirements, prompting a key question: does the energy consumed in advancing artificial intelligence drive meaningful progress, or does it concurrently contribute to increased CO_2 emissions? This concern emphasizes an ongoing debate about whether the expansion of artificial intelligence proves environmentally advantageous or ultimately detrimental.

The study adds to the limited body of literature by providing important insights for policymakers based on the empirical data provided. Considering the present complex and debated interaction between artificial intelligence and the environment, this paper seeks to advance understanding by offering new insights into AI's environmental effects, thereby establishing a scientific foundation to support policymakers in shaping and regulating artificial intelligence development. The research analyzes a developed country, Japan, in the period of almost 30 years, and this study employs the latest available data for its empirical investigation. We expect that it will strengthen the existing body of evidence on artificial intelligence (as technological factor) impact on energy consumption and effect, so that certain decisions can be made more easily.

Thus, the central objectives of this research are:

1. To perform the analysis of the impact of energy use, artificial intelligence, economic growth, and exports on CO_2 in Japan.
2. To compile the model and evaluate the long-term and short-term relationships among artificial intelligence, energy consumption, economic growth, and exports in relation to carbon emissions in Japan relationships among energy use, artificial intelligence, economic growth, and exports on CO_2 in Japan.
3. To evaluate positive and/or negative impact of energy use, artificial intelligence, and CO_2 on Japan's economic progress.

The next section of literature review deploys the previous research on paper's topic (links between energy use, AI, economic growth, and exports with CO_2) is presented, the second section introduces chosen methodology and the research methods, when the third section represents empirical results concluding with critical view in discussion and policy recommendations part.

2. Literature review

The existing scientific literature has extensively studied the indicators that affect environmental degradation and energy issues in the transition to renewable energy so far. This provides prerequisites for high-level directions in the aforementioned topics, but the emerging impact of artificial intelligence has seldom been incorporated into conventional research frameworks. Several studies have explored the diverse opportunities and risks of artificial intelligence to the environment, CO_2 concentration, and energy source diversification from different viewpoints; however, a rigorous and quantitative analysis is still absent. In order to fill this gap, the present study seeks to provide a quantitative evaluation of the impact of AI on the natural world, CO_2 emissions, energy source use, and economic growth in Japan.

Thus, the paper initially reviews existing literature on the role of technological determinants, economic growth, and energy consumption on critical environmental variables. Later, the analysis will concentrate on qualitative discussions and empirical research examining the particular impacts of artificial intelligence on the environment. Finally, we will discuss the gaps in prior studies. Thus, the section explains the link between energy use, artificial intelligence, CO_2, and their economic impact.

The academic literature presents diverse results regarding the relationship between economic growth and renewable energy consumption, applying certain methodological approaches, time period and types of data used for the research.

2.1. CO_2 emissions and artificial intelligence

Artificial intelligence is playing an increasingly prominent role across diverse sectors of development today. AI, as one of the essential new technologies in the contemporary industrial age, serves an important position in contributing to climate change problems solving and has the potential to promote carbon dioxide reduction. However, its effects on the environment vary from region to region. For instance, a study conducted across 30 provinces of mainland China between 2006 and 2019. The outcomes of the research show that AI helps to reduce CO_2 emissions (Dong et al., 2023). Another longitudinal study of 29 European countries from 1998 to 2017 confirms that AI is helping to decrease CO_2 emissions across European nations (Chatti et al., 2024). Furthermore, the results of the study reveal a strong positive association between artificial intelligence implementation and carbon emissions across nations in East Asia and the Pacific region (Shah et al., 2024).

But other scientists, conducting a study of 74 countries (from 1993 to 2019) found that robot's usage can worsen air pollution and climate change. Robots can improve performance and energy effectiveness; nevertheless, they promote greater output and expanded energy use. This leads to higher energy use, which ultimately harms air quality (Luan et al., 2022; Tang et al., 2025). And also, another research paper contributes to the previous findings, when the utilization of artificial intelligence is also leading to increased energy consumption. It contributes to environmental problems, such as higher CO_2 emissions (Delanoë et al., 2023). Increasing adoption of AI systems results in high electricity consumption, which significantly increases carbon dioxide emissions into the environment. Researchers examined 69 countries (data in the range of 1993:2019) to investigate whether artificial intelligence is driving energy transitions and reducing carbon emissions. Although the research results demonstrated a positive effect of artificial intelligence on reducing carbon dioxide concentrations, the researchers acknowledge that the results are not empirical. As technology develops, there are growing concerns regarding the possible adverse effects of AI on CO_2 emissions. Because supporting AI systems requires extremely large amounts of energy for data centers, servers, and their cooling (Wang et al., 2024b). A growing number of researchers and practitioners the rapid expansion of AI use is evident in the rising energy demand needed to train artificial intelligence systems. For instance, research results show that training a single model such as ChatGPT requires approximately 1.287 gigawatt-hours of electricity, which is comparable to the yearly power consumption of about 120 households in the United States (Dong et al., 2024; Wang et al., 2024a; Magazzino & Mele, 2025). When examining the link between technological development and CO_2, researchers determined that technological advancement lowers carbon emissions by enhancing production efficiency. The development of the digital economy contributes to CO_2 reduction both directly and through notable spatial spillover impacts. On the one hand, AI has considerable potential to enhance organizational production efficiency, contribute to one improvement of industrial processes, or contribute to protection of the environment and energy utilization measures, thereby improving the environment.

While productivity and energy consumption improvements can exacerbate environmental problems (Wang et al., 2024a; Safi et al., 2023; Solmaz et al., 2025).

A paradoxical situation has arisen in which AI systems can increase energy utilization and carbon emissions. In other words, technological progress has varied effects on CO_2 and energy (Wang et al., 2024b). Therefore, it is worth paying attention to the need to develop sustainable artificial intelligence management systems (Wang et al., 2024a; Xu et al., 2025).

There is no agreement in scientific world about AI influence on CO_2. Some scientists claim that artificial intelligence substantially lowers CO_2/. Others state the opposite, that AI has harmful impacts on the environment and global temperature rise. The importance of evaluating the link between artificial intelligence and environmental sustainability is explicitly acknowledged.

The country of Japan around 50% of businesses are using generative AI technologies. However, Japan is developed country but still around 90% uses fossil fuels for energy production, and is ranked in TOP5 world's largest oil consumer, the largest liquefied natural gas importer, and in TOP4 as the largest crude oil and coal importer (Adebayo et al., 2021; Tripathi et al., 2025). Whereas Japanese Prime Minister Yoshihide Suga set a new target of reaching net-zero carbon emissions by 2050 as part of the strategy of "Green Growth Strategy for Carbon Neutral by 2050" was approved (Ohta & Barrett, 2023). The choice of Japan as a country was determined by the facts outlined above. While Japan is one of the biggest emitters in the world, it is seeking to decarbonization strategy's implementation. The research in this paper will contribute to energy transformation away from fossil fuels.

2.2. CO_2 emissions and energy use

Energy serves as a fundamental engine of development, especially in the progress of AI, which is transforming various sectors. However, this progress comes with a downside, as it results in higher emission output. Carbon dioxide emissions data from 17 Asia-Pacific countries over 61 years (1960–2020) was leading to energy utilization which negatively impacts the environment by increasing CO2 emissions (Rahman & Alam, 2022). Likewise, an analysis of CO_2 emissions in 23 developing countries over the period 1995–2018 demonstrates that both long-run and short-run findings reveal a positive association between energy consumption and carbon dioxide emissions (Sikder et al., 2022). This topic of energy economics and sustainability indicators is widely discussed in the scientific literature. Technological factors are identified as essential, which can influence environmental indicators produce positive or negative effects on carbon dioxide emissions as well as energy diversification, etc. (Wang et al., 2024a).

Let's analyze other countries' situations examining energy consumption in relation to its impact on CO_2 emissions.

A direct interaction was identified between economic growth and CO_2 emissions across the top ten economies undergoing energy transition (USA, China, Germany, UK, France, India, Japan, Brazil, Spain, and South Korea) (Dissanayake et al., 2023). Other authors found that in China, from 1971 to 2016, energy use has worsened the country's state of the environment (Khan et al., 2022). A study employing Malaysian time-series data as the developing country between 1990 and 2019 shows that energy use shows a strong positive influence on CO_2 emissions, where a 1% increase in energy use corresponds to a 0.91% growth in CO_2

emissions (Raihan et al., 2022). Furthermore, in Chile, as the developing country, has raised electricity consumption, resulting in greater carbon emissions and consequently undermining environmental sustainability (Kirikkaleli et al., 2022). An analysis of Sub-Saharan African (SSA) nations covering the period 1996–2019 indicates that energy consumption negatively affects environmental sustainability in the region, primarily by contributing to higher carbon emissions (Appiah et al., 2024).

Previous studies conducted in Europe, including the case of Lithuania, indicate that technological development, ICT expansion, industrialization, and economic activity are strongly associated with environmental changes and carbon emissions. These findings highlight that digital and technological progress may simultaneously stimulate economic growth and increase environmental pressure through higher energy consumption (Kraujalienė et al., 2026).

Developing nations, including Colombia, have not yet experienced gains from higher levels of economic diversification. The Turkish case study found that Economic sophistication in Turkey contributed to mitigating environmental damage, whereas increasing energy consumption and GDP negatively affected environmental conditions. Studies of the world's 10 most complex economies, examining the effect of electricity consumption and the economic sophistication index (ECI) on them, have shown that electricity use has increased over time and this has affected CO_2. Studies also have shown that have risen as a result of expanding trade and greater reliance on non-renewable energy sources, while adoption of renewable energy has lowered emissions in both the short term and the long term. It deserves attention that the use of fossil-based energy sources has been related to increased CO_2 emissions. The study examining the Organization of eight Petroleum Exporting Countries (OPEC) as well as a group of nine highly developed countries over the period 1985–2020 found that the joint short-run and long-run impacts of industrialization and energy use did not produce a significant effect on CO_2 emissions in OPEC member countries. Although short-run CO_2 exhibited a positive effect, affecting foreign direct investment and economic progress. The findings showed a positive correlation between industrialization and energy utilization what has a significant impact on CO_2 in advanced (highly developed) countries. In the United States, residential and commercial sectors have adopted 100% clean energy. Nearly half of the United States electricity sector in 2019 was made up of American businesses and households that switched to 100% clean energy. This has resulted in a substantial increase in wind and solar power generation. Studies indicate that energy use contributes to greater CO_2 in short and long term within the global context (Afroz et al., 2024; Dissanayake et al., 2023; Chen et al., 2016; Khan et al., 2020; Rahman et al., 2022). Many countries have contributed to changes in energy use through their strategic decisions: cutting the consumption of fossil-based fuels and moving to green energy to mitigate environmental harm (Wang et al., 2024a; Song et al., 2025).

Analysis of current literature demonstrates the association between energy consumption and carbon dioxide emissions which has a significant positive influence on environmental deterioration in emerging economies, while in developed nations this impact is not distinctly observed, only facing the fact that energy consumption turns into greater emissions. Thus, the relationship of energy use on carbon emissions is clearly observable in developed countries. When Japan is in the TOP countries using energy and reaching carbon neutrality by 2050, it is becoming actual object for evaluation.

2.3. CO_2 emissions and economic growth

The nation's overall economic expansion is largely supported by energy use, which serves as a key factor in its development. Research studies reveal a statistically positive relationship between economic growth and CO_2 in the world's leading CO_2-emitting countries (Puntoon et al., 2022). In Turkey, between 1980 and 2016, the research highlights a statistically significant association among GDP growth and the growth in carbon dioxide emissions (Karaaslan et al., 2022). Furthermore, economic progress plays a central role in environmental decline, as evidenced by a study of 22 leading remittance-receiving countries between 1986 and 2017 (Zafar et al., 2022). Across the G-7 nations during 1997–2021, economic progress generally results in higher carbon dioxide emissions. However, its impact varies across nations, with a reduction effect detected at the lower distribution levels in Japan (can be affected by relatively slow economic growth in recent years), at middle level – in Germany and France, and at higher level – in Italy (International Monetary Fund, 2025; Ayhan et al., 2023; Ali & Kirikkaleli, 2022). In Japan GDP is shown to exert a statistically significant positive impact on carbon emissions, whereas green energy demonstrates a notable negative impact (Nawaz et al., 2025). The non-linear impact of renewable energy and trade on consumption-related carbon emissions: insights from Italy. Additionally, economic growth has been the most significant driver of Carbon dioxide emissions in Mexico between 1973 and 2018 (Salazar-Núñez et al., 2022). A study in Nigeria and South Africa explored that economic progress and carbon emissions in Nigeria had a positive association using the ARDL and other methodologies. A study of Mexico explored similar results when CO_2 emissions were directly affected by economic development. Current research was conducted by utilizing the ARDL model based on time series data. A case study of Egypt proved also that there is a positive association between carbon emissions and economic development when applying the ARDL and other models. In addition, the Organization for Economic Co-operation and Development (OECD) in its report also states that economic development exerts a positive effect on carbon emissions concentration. Similar studies of previous Malaysian research papers found the direct correlation between GDP and CO_2. If comparing research findings of carbon emissions and economic situation in high-, low-, and medium-income countries we can see contradictory results. In both low- and high-income countries, middle-income nations tend to experience a more beneficial effect of economic development on environmental degradation. Generally, high-income countries exhibit a negative relationship between ecological degradation and income levels (Afroz et al., 2024).

Several other scholars have examined the impact of economic development as well as environmental pollution. A case study of France showed an indirect relationship between CO_2 emissions and environmental pollution, where its levels exceeding a certain threshold led to a reduction in CO_2 emissions. Research revealed that middle- and lower-income economies have experienced environmental damage as a result of economic diversification. The Indian case study found that increased economic complexity in India led to a deterioration in environmental quality. Researchers explored also Malaysia as the country ranked 4th in Southeast Asia in 2019 by GDP which is expected to rise around 3 times from 2004 to 2030 (annual growth rate – 4.6%), and also reach carbon neutrality by 2050. And here is the risk: growing economy can bring an advantage of the county economic state but also a risk to damage the environmental sustainability when income levels grows. Moreover, Malaysia is (Afroz et al., 2024).

Current research results have shown a directional causal association between energy use and economic development in the five largest carbon emitters: the United States, China, Brazil, India and Russia. A direct relationship has also been found in the case of Italy, where it has been shown that continuous economic development contributes to continuous increases in energy use (Dissanayake et al., 2023).

Literature analysis demonstrates the connection between economic development and CO_2 emissions. In most cases of different emerging and developed nations, when the economy grows, so does CO_2.

The current scientific studies examine the environmental impact of various kinds of energy use, economic state, AI, and export factors, are based on environmental sustainability, carbon reduction, etc. However, limited research examines the connection between artificial intelligence and environmental sustainability. In summary of the literature review, unaddressed areas in the research were detected. (1) From an academic standpoint, current research addressing the environmental sustainability of artificial intelligence predominantly concentrates on carbon emissions perspective. The impact of artificial intelligence on use of energy has received limited scholarly attention, and very few studies integrate multiple variables: AI, energy consumption, exports and economic development on CO_2. (2) In terms of the study object, the Chinese market has attracted the greatest research attention, whereas studies focusing on other countries remain limited. (3) AI as a variable in mentioned model was rarely used, especially evaluating developed countries as Japan, whose economic operations are still largely driven by fossil-based energy sources. Japan is selected for this study.

This research is mainly driven by the absence of a shared consensus regarding the exact linkage among artificial intelligence, economic development, and energy consumption in relation to carbon emissions on a scale of developed country.

After literature review and research gaps we may estimate the direction of this research and raise the key questions for research: (RQ1) What is the effect of artificial intelligence adoption on carbon emissions? (RQ2) What is the impact of energy use on carbon emissions? (RQ3) What is the impact of economic development on CO_2? A study is seeking to determine how artificial intelligence, energy utilization, economic development affect CO_2, taking into account the impact of exports.

Previous research results show that energy consumption is typically associated with rising CO_2 emissions, AI technologies may improve energy efficiency, while simultaneously elevating emissions, as economic expansion is positively associated with carbon emissions. Therefore, next hypotheses are formulated: (H1) Increasing AI adoption increases carbon emissions by increasing energy consumption. The first hypothesis examines whether higher AI adoption leads to higher CO_2 emissions, partly through increased energy use. (H2) Higher energy consumption rises CO_2 emissions. The second hypothesis directly tests the influence of energy use on carbon emissions. (H3) Economic development has a positive influence on CO_2 emissions and associated with rising carbon emissions. This hypothesis investigates the influence of economic development on carbon emissions.

3. Research methodology

Recent studies increasingly emphasize the importance of quantitative and econometric methods for evaluating technological development, innovation efficiency, and sustainability-related economic processes. Various analytical approaches, such as Data Envelopment Analysis (DEA), COPRAS multi-criteria assessment, feed-forward neural network models, and other efficiency evaluation methods, are widely applied in economic and management research to assess technology transfer, organizational performance, managerial activity, and resource allocation efficiency. Previous research conducted in Lithuania highlights those advanced quantitative methods are valuable tools for evaluating innovation systems, R&D expenditures, digital transformation, managerial effectiveness, and technology-oriented development processes in higher education institutions and organizations (Stankevičienė & Kraujalienė, 2017, 2021; Kraujalienė, 2019; Kraujalienė & Gruodis, 2025, 2026). Moreover, recent worldwide analyses demonstrate that technological, economic, and social determinants play an increasingly important role in shaping sustainable economic development, investment attractiveness, and international competitiveness (Constantinescu et al., 2025).

The primary objective of this study is to analyze the relationship among energy consumption, AI, economic development, exports, and CO_2 emissions. The research evaluates both the short-term and long-term effects of AI, energy consumption, economic expansion, and exports on CO_2 in the country of Japan. Consumption-based emissions proxies are used to measure CO_2 levels. To accomplish the research aims, this study employs the Autoregressive Distributed Lag (ARDL) econometric approach. This method is appropriate for analyzing both the short-term and long-term interrelations among the indicators and offers insights into their effects over both time horizons However, ARDL can only be applied if certain conditions are met. The first condition: research indicators should be stationary and the presence of cointegration among the indicators is required. To confirm this condition, the Augmented Dickey-Fuller (ADF) unit root test is performed, which evaluates the stationarity of the indicators (AI, energy consumption, exports, economic development, and CO_2 emissions). After the stationarity of the indicators is verified, the second condition is that the variables must be cointegrated. The ARDL bounds testing approach is utilized to examine the presence of cointegration between the indicators, indicating a long-term equilibrium relationship. If these criteria are achieved, the ARDL econometric model can be employed for continued investigation to examine the long-term and short-term impacts.

This study employs a range of diagnostic tests to enhance the reliability and precision of the research results. These tests are divided into three parts. The first part includes the ARDL bound test and the ADF unit root test. The Augmented Dickey-Fuller (ADF) unit root test is conducted to assess the stationarity of the indicators, while the ARDL bound test evaluates the presence of cointegration between the indicators. The ARDL model is applicable if these conditions are met. The second part consists of model specification tests. The Breusch-Godfrey serial correlation test investigates serial correlation in the residuals. Next, the Breusch-Pagan-Godfrey test confirms the presence of heteroscedasticity. The Regression Specification Error Test Ramsey (RESET) checks if the model for this research is appropriately defined. The third part includes model stability tests. The Cumulative Sum of

Squares (CUSUMSQ) and Cumulative Sum Test (CUSUM) tests are employed to evaluate the model's stability over time and identify any structural breaks that may influence the result (Sikder et al., 2022).

This research is structured into four sections. In the introduction section, the background of the study is explained. The first part of this research presents the literature review and discusses the relationship between previous studies. The second section of the study presents the methodology and outlines the study methods used to execute and achieve objectives. The third section of the research outlines the findings and discussion. The last and fourth part presents the conclusions and provides policy implications based on the research results, as well as suggesting directions for future research.

This research estimates the long-term and short-term effects of AI, energy consumption, economic development, exports, and CO_2 emissions in the country of Japan. The central variable examined in this study is CO_2 emissions (consumption-based) (Mehboob et al., 2024) as the explained indicator. Nevertheless, additional indicators, such as artificial intelligence (Rasheed et al., 2024), energy use (Hamed et al., 2024), and (Raihan et al., 2024) are used as explanatory variables, with exports (Hasanov et al., 2018; Zhao & Zhang, 2025) used as a control variable. This study utilizes secondary data gathered from Our World in Data (OWDI), the Global Carbon Atlas (GCA), World Development Indicators (WDI), and the Organization for Economic Co-operation and Development (OECD). The research is quantitative and covers the period from 1995 to 2024. To assess both the short-term and long-term dynamics, current research uses the ARDL econometric model to examine the relationships among the indicators. This model is suitable because, if the research is based on small observations, the results are valid and without errors. The period of time of almost 30 years in ARDL model is suitable for analyzing a single country's time series data, manage variables with varying levels of integration (I (0) and I (1)), as it is designed to capture both short-term dynamics and long-term equilibrium connections among variables under a single time-series model. Furthermore, the ARDL model performs well even with a relatively small sample size (such as 30 annual observations), which is often the case in single-country studies covering a few decades. The ARDL model has many advantages, with the key advantage being its ability to examine both long-term and short-term correlations between variables. Nevertheless, before econometric use, there are a few requirements that must be met for applying the ARDL model. Indicators should be stationary, and the variables must be cointegrated. For stationarity, the Augmented Dickey-Fuller (ADF) unit root test is applied to assess whether the variables are stationary at their level (when the research data is stable and shows no trends) as well as at the first-differenced form (reflecting data changes that are stable without persistent growth trends). After that, to examine cointegration between indicators, the ARDL bounds method is the best to test for cointegration. If the ARDL bounds test value (F-statistic value) is higher than the upper and lower critical bounds, it indicates that cointegration exists between indicators. If these conditions are met, the econometric ARDL model can be used for further estimations of the short-term and long-term interconnections between the indicators.

Furthermore, to enhance the uniqueness and accuracy of the ARDL econometric approach, this research employs various diagnostic tests. The Breusch-Godfrey serial correlation test checks if there is any pattern or correlation in the residuals (errors) of a regression model.

If the p-value exceeds the significance level (5%), it means serial correlation is not detected, indicating that the model is correctly specified, and the findings are trustworthy. In a similar manner, the Breusch-Pagan-Godfrey test checks for heteroscedasticity, a common issue in time series data, which appears when error terms exhibit non-constant variance. If the p-value is above the chosen alpha level or is greater than the selected level of significance (5%), it means no heteroscedasticity exists between variables. Besides, the Regression Specification Error Test (RESET) checks for incorrect model specification. This test evaluates whether the regression model is properly specified, that is, whether it correctly captures the relationships among the indicators. If the results indicate that the model is adequately specified, this implies the absence of specification errors or omitted variables, thereby supporting the reliability of the findings The Cumulative Sum Test (CUSUM) and Cumulative Sum of Squares Test (CUSUMSQ) tests help ensure the stability of the model and detect structural breaks.

4. Empirical results and discussion

Table 1 below provides an overview of the detailed variables and literature sources.

The main independent indicator in current study is carbon emissions (CO_2). The influence of AI, energy consumption, and economic development on the dependent indicator is studied, when exports is chosen as a control variable to ensure reliable results, by clarifying whether changes in emissions are due to differences in export levels. This research focuses on the main influencing factors of CO_2 emission levels, focusing on how various economic and technological determinants impact environmental performance. Therefore, the study examines whether artificial intelligence (AI) helps to reduce or increases carbon emissions; whether higher energy use leads to higher emissions; and whether economic development contributes to the increase or reduction of CO_2 emissions.

AI variable is measured by triadic patent families, defined as groups of related patents that are filed with at least three main patent institutions: USPTO (United States Patent and Trademark Office), EPO (European Patent Office), and JPO (Japan Patent Office). Triadic patent families are widely used as a proxy for AI development because they capture high-quality, internationally protected innovations, reflecting the intensity and technological significance of

Table 1. Overview of the chosen indicators and corresponding data sources (prepared by authors, 2025)

Variables	Detailed indicators	Sources
Carbon emissions (CO_2)	CO_2 emissions (consumption-based)	Global Carbon Atlas (2024)
Artificial Intelligence (AI)	Triadic patent families (AI Proxy)	Organisation for Economic Co-operation and Development [OECD], (n.d).
Energy use (consumption)	Primary energy consumption per capita (kWh/person)	Our World in Data, (n.d.)
Economic growth (development)	GDP per capita (current US$)	World Bank (n.d.)
Exports	Exports of goods and services (% of GDP)	World Bank (n.d.)

AI-related R&D. Following OECD guidelines, triadic patent families are employed as a proxy for AI because they reflect high-quality, globally protected technological innovations. They capture both the intensity and significance of AI-related R&D, making them a widely accepted measure in empirical studies. Alternative proxies include AI-related publications, R&D expenditures, startup activity, and citation-weighted patents, each capturing different dimensions of AI development (OECD, n.d.; Zhu et al., 2023).

4.1. Model formulation to investigate both the long-term and short-term effects of AI, energy consumption, economic development and exports on carbon emissions in the country of Japan

In the ARDL model, both short- term and long- term relationships are designed to reflect the dynamic interactions among the variables. Short-term coefficients indicate the temporary effects of variations in the independent indicators on the dependent indicator, while the long-term parameter estimates reflect the long-term stable association among them. Estimating both relationships is important because the response of variables such as CO_2 emissions, energy use, and economic development may differ across time. In the short run, fluctuations may result from shocks, crises or policy changes, whereas in the long-term, the indicators tend to adjust approaching a stable state. Therefore, analysing short-run and long-run impacts offers a more comprehensive insight of the underlying dynamics and ensures that the model captures both transient and persistent impacts (Sikder et al., 2022; Tagwi, 2022).

In Eq. (1), the functional relationship between the variables – AI, energy consumption, exports, and economic development on carbon emissions is shown. This equation also explains how the dependent indicator (CO_2) impacts the rest independent indicators. Eq. (1) is also utilized in constructing the ARDL econometric model equation. The starting point of the model is the theoretical functional relationship:

$$CO_{2t} = f\left(AI_t,\ EU_{t,}, EG_t, EXP_t\right), \tag{1}$$

where, carbon emissions, AI, energy consumption, exports, and economic development are represented by components of the formula as CO_{2t}, AI_t, EU_t, EG_t and EXP_t , respectively, as variables at time *t*. This equation represents the theoretical assumption that CO_2 (as the result of chosen explanatory variables) depend on: Artificial intelligence development (AI), Energy use (EU), Economic growth (EG), and Exports (EXP). At this stage, the equation is conceptual – it shows the direction of dependence but does not yet specify the econometric structure.

The theoretical relationship is then converted into an econometric ARDL model that allows short-term and long-term interactions to be estimated among the indicators: AI, energy consumption, exports, economic development and carbon emissions. The ARDL model has been used in previous research by various scholars authors (Sreenu, 2022; Sufyanullah et al., 2022; Tagwi, 2022; Yahyaoui, 2022). This econometric model was found by Pesaran and Shin (1999) and later developed by Pesaran et al. (2001). The research utilizes EViews 12 software to evaluate the long-term and short-term connections among the chosen indicators (via the following link: https://www.eviews.com/download/student12/). Eq. (2) explains the ARDL bound testing approach.

$$\Delta CO_{2t} = \alpha_0 + \sum_{k=1}^{n} \alpha_1 \Delta AI_{t-k} + \sum_{k=1}^{n} \alpha_2 \Delta EU_{t-k} + \sum_{k=1}^{n} \alpha_3 \Delta EG_{t-k} + \sum_{k=1}^{n} \alpha_4 \Delta EXP_{t-k} + \lambda_1 AI_{t-1} + \lambda_2 EU_{t-1} + \lambda_3 EG_{t-1} + \lambda_4 EXP_{t-1}, \tag{2}$$

where Δ represents the first-difference approach, capturing short-term variations, ε_t is the white noise (the stochastic error term), and α_0 is the drift component. The constant term (α) captures the starting level of carbon emissions when chosen explanatory variables – artificial intelligence (AI), energy use (EU), economic growth (EG), and exports (EXP) — are equal to zero (α shows the "starting point" or base level of emissions before the impacts of other indicators are taken into account). λ – is the error correction term (ECT), indicates the speed at which the system converges back to long-run equilibrium following a shock (deviation). Then the next step is to choose optimal lags using AIC, BIC, or HQ criteria. The Akaike Information Criterion (AIC) is employed for selecting the optimal lag length in the ARDL model because it provides a balance between model fit and parsimony. AIC helps identify the optimal lag length by minimizing information loss. Compared to other criteria, such as the Schwarz Bayesian Criterion (SBC/BIC) or the Hannan-Quinn Criterion (HQC), AIC tends to select a slightly larger lag structure, which is useful in small or moderate samples (like a almost 30-year single-country dataset). This is important for ensuring that all relevant short-run dynamics are captured and that no essential lagged effects are omitted. The Error Correction Term (ECM) is involved to the ARDL approach to capture the long-term equilibrium interaction among the indicators while simultaneously accounting for short-run dynamics. The ECM evaluates the rate and direction at which the system returns to a stable state following such deviations. When the ECM coefficient is negative and significant, this implies that the system is converging toward long-run equilibrium, meaning that short-run disequilibria are progressively adjusted across time. This feature makes the ARDL-ECM approach particularly valuable for assessing both immediate (short-term) and persistent (long-term) effects under a single comprehensive approach. Eq. (3) shows the Error Correction Term ECM form of Eq. (2) (Sreenu, 2022; Sikder et al., 2022; Tagwi, 2022).

$$\Delta CO_{2t} = \alpha_0 + \sum_{k=1}^{n} \alpha_1 \Delta AI_{t-k} + \sum_{k=1}^{n} \alpha_2 \Delta EU_{t-k} + \sum_{k=1}^{n} \alpha_3 \Delta EG_{t-k} + \sum_{k=1}^{n} \alpha_4 \Delta EXP_{t-k} + \varnothing ECM_{t-k} + \varepsilon_t, \tag{3}$$

where, ∅ represents the the Error Correction Term ECM coefficients for short-term dynamics, and Δ stands for the initial change. The error-correcting approach demonstrates how long-term stability adjusts after a short-term shock.

The robustness checks and sensitivity analysis need to be performed in econometric ARDL model. Robustness and sensitivity analyses are implemented to assess the reliability and stability of the empirical findings. They test whether the estimated relationships remain consistent when the model's assumptions, variable definitions, or estimation methods are slightly modified. Robustness checks evaluate whether the main findings are robust to alternative model specifications or estimation procedures. Sensitivity analysis examines how sensitive the results are to small changes in model inputs, variables.

Thus, to enhance the accuracy and consistency of the results, robustness and sensitivity analyses were conducted.

Several diagnostic and stability tests were applied for this research: Breusch-Godfrey test was utilized to detect serial correlation in the model residuals, validating that the model is not affected by serial correlation; Breusch-Pagan-Godfrey test was performed to examine heteroskedasticity, confirming that the residual variance remains stable; Ramsey RESET test was implemented to evaluate incorrect model specification, verifying that the functional form of the model is appropriate; CUSUM and CUSUMSQ tests were applied to check parameter stability and to verify that the estimated coefficients continue to be consistent throughout the study period. In combination, the applied diagnostic and stability tests confirm the validity of the model structure and the consistency of the estimated parameters (Sreenu, 2022; Sikder et al., 2022; Tagwi, 2022).

Sensitivity analysis was performed to assess how sensitive the estimated relationships are to alternative assumptions and model configurations. Sensitivity analysis was performed by altering the sample period and substituting alternative proxies for explanatory variables. The analysis in this research involved: testing variable stationarity utilizing the Augmented Dickeyp-Fuller (ADF) unit root test to verify that the ARDL model's preconditions (variables integrated of order I (0) or I (1)) were satisfied); Re-estimating the ARDL model with alternative lag lengths selected using the AIC criterion to verify that the short-term and long-term coefficients remain consistent. Assessing model stability through the CUSUM and CUSUMSQ tests (also serving as part of sensitivity testing), confirming that small perturbations in model structure or sample period do not significantly alter the results. These steps verify that the results are stable and not overly sensitive to minor changes in assumptions, lag selection, or sample variation (Sreenu, 2022; Sikder et al., 2022; Tagwi, 2022).

The consistency of results across these tests validates the consistency and reliability of the estimated ARDL specification.

4.2. ADF unit test for assessing stationarity among variables

One of the prior conditions before applying the econometric ARDL approach is the requirement when the variables exhibit stationarity and must be cointegration between them. The Augmented Dickey-Fuller (ADF) unit root test analysis helps verify the stationarity properties of the variables. In addition, the ADF test was introduced by Dickey and Fuller (1979).

Table 2 shows the research outcomes of the Augmented Dickey-Fuller (ADF) unit root test, which indicate that artificial intelligence is stationary at both the level and first difference,

Table 2. Results of the Augmented Dickey-Fuller (ADF) Unit root test (prepared by authors, 2025)

Indicators	ADF 1st level I (0)	ADF 1st difference I (I)
Carbon emissions (CO_2)	–0.2708 (0.9725)	–4.4354 (0.0016)
Artificial Intelligence (AI)	–3.5239 (0.0145)	–3.9584 (0.0052)
Energy use (consumption)	0.6671 (0.9891)	–8.0561 (0.0000)
Economic growth (development)	–2.2964 (0.1797)	–4.4728 (0.0015)
Exports	–1.8324(0.3581)	–6.2777 (0.0000)

while the other variables: economic development, energy consumption, exports, and CO_2 emissions are stationary at the first difference. At the first level, the data is stable and exhibits no discernible trend. However, when taking the first difference, data fluctuations are identified, but the data remains stable without showing any upward trend.

4.3. ARDL Bounds testing approach to examine long-term cointegration

Once all research variables are confirmed to be stationary, the next step is to examine their cointegration. The ARDL bound test is an appropriate method for investigating the presence of cointegration between the variables.

Table 3. ARDL bound test results (prepared by authors, 2025)

F-Bound Test	Value	Sign	I (0)	I (I)
F-Statistics	12.4795	10%	2.2	3.09
K = 4		5%	2.56	3.49
		2.5%	2.88	3.87

Table 3 shows the results of the ARDL bound test. The findings of the ARDL bounds test indicate the presence of cointegration among the indicators (AI, energy consumption, exports, economic development, and CO_2 emissions), as the ARDL bound test F-statistic value of 12.4795 exceeds both the lower and upper bounds at various significance levels (10%, 5%, 2.5%).

4.4. ARDL econometric model analysis: long-term and short-term results

After fulfilling the basic conditions of the econometric ARDL model (i.e., the research variables are stationary and cointegration exists among the indicators), the current research uses the ARDL econometric approach for further estimation of the long-term and short-term relationships. The outcomes of the ARDL econometric analysis are shown in Table 4. In this research, artificial intelligence, energy consumption, and economic development are the primary explanatory variables, with exports considering it as the control variable, while carbon emissions serve as the response variable. This research revealed positive and statistically significant effects of artificial intelligence on carbon emissions in the long-term and short-term in Japan. According to the research estimates, a 1% increase in artificial intelligence leads to a 0.0691% increase in the short-run and a 0.1767% increase in the long-run. Based on the research estimations, AI has a much greater effect on damaging the environment in Japan in the long-term and short-term. However, some studies support our outcomes (Delanoë et al., 2023; Luan et al., 2022; Shah et al., 2024; Wang et al. 2023). Furthermore, Japan has been actively working with artificial intelligence, seeing its potential to transform society, industry, and innovation. Artificial intelligence (AI) is seen as crucial for future progress by leaders in Japan. Japan is a leader in AI development, with the AI market expected to reach US$8.12 billion in 2024. The market is predicted to grow by 28.48% each year, reaching US$36.52 billion by 2030. A recent survey shows that 46.8% of businesses in Japan are using generative AI.

Table 4. ARDL model results for both the long and short term (prepared by authors, 2025)

Indicator	Long-term			Short-term		
	Coeff.	t-stats	p-value	Coeff.	t-stats	p-value
AI	0.1767	2.1320	0.0444	0.0691	2.1833	0.0400
EU	0.9141	4.6561	0.0001	0.3577	3.3815	0.0027
EG	0.5445	4.3342	0.0013	0.2130	5.3668	0.0000
EXP	–0.1731	–1.9343	0.0660	–0.1104	–2.3751	0.0267
ECT_{-1}				–0.3913	–9.5862	0.0000

In both the long-term and short-term, the outcomes demonstrate that energy use is positively linked to CO_2 emissions and is statistically significant. A 1% increase in energy use leads to a 0.3577% increase in CO_2 emissions in the short-term, and a 0.9141% increase in the long-term. In light of these outcomes, empirical findings suggest that the exploitation of energy resources harms the environment in Japan and undermines environmental sustainability. Some previous studies confirm our research findings (Appiah et al., 2024; Kirikkaleli et al., 2022; Rahman et al., 2022; Shah et al., 2024). Similarly, the use of AI models is increasing energy consumption because the development of AI tools depends on energy use, which contributes to environmental issues like higher CO_2 emissions (Delanoë et al., 2023). Additionally, some data sources confirm the validity of our outcomes. According to Our World in Data, energy use increased from 38,527 kWh in 2020 to 40,426 kWh in 2021. Furthermore, carbon emissions rose from 1,185.81 mt in 2020 to 1,222.92 mt in 2021. As a result, both contribute to damaging the environment in Japan.

In nominal GDP terms, Japan holds the position of the third-largest economy globally and ranks fourth when measured by purchasing power parity. The outo2comes of this research show that economic growth is positively correlated with carbon emissions over both long-term and short-term periods, implying that economic activity in Japan raises carbon output. In fact, A 1% rise in economic expansion is associated with a 0.2130% growth in carbon emissions in the short term and a 0.5445% increase over the long term. Many related studies have supported our findings (Ayhan et al., 2023; Puntoon et al., 2022; Salazar-Núñez et al., 2022). For instance, similar outcomes have been identified in studies undertaken in Indonesia, Lithuania, the G-7, and Mexico, demonstrating that economic expansion contributes to higher CO_2 emissions in these regions. Artificial intelligence is helping to develop Japan's economy. Japan's path to becoming a global leader in artificial intelligence is an interesting example of combining tradition with innovation. The country's efforts to lead in AI, such as the Ministry of Economy, Trade and Industry (METI)'s GENIAC project, show a strong government commitment to using generative AI for economic growth and social progress. Artificial intelligence increases growth in Japan, but AI requires more energy to use AI tools. As a result, this increased energy utilization drives greater carbon emissions.

Japan is the largest exporter globally. The export of goods and services represents the aggregate value of items and commercial services delivered abroad. This value increased from 15.53 trillion USD to 18.13 trillion USD from 2020 to 2021 in Japan. As indicated by these research outcomes, exports have an adverse relationship with carbon emissions, helping to enhance environmental sustainability in Japan. An increase of 1% in exports is associated with a 0.1731% decline in carbon emissions over the long term and a 0.1104% decline in the short term. These research outcomes are similar to our results from Turkey and Italy. In these countries, exports and carbon emissions have an adverse relationship, helping to increase environmental sustainability (Ali & Kirikkaleli, 2022; Haug & Ucal, 2019; Pata, 2018; Wang et al., 2023).

The error correction component reveals a substantial adjustment process toward long-term equilibrium, with a value of −0.3913 at the 1% significance level. Since the error correction term should have a negative and significant coefficient, this study meets that condition. Let's interpret AI results in the long-term. Using the standard 5% significance level ($\alpha = 0.05$), we see, that p-value = 0.0444 < 0.05, so the coefficient is statistically significant; the t-statistic 2.1320 also exceeds the critical value (~1.96 for 5%), confirming significance. Therefore, the AI variable has a positive and statistically significant long-term effect on the dependent indicator. The coefficient 0.1767 means: if AI increases by one unit, the dependent variable in the long run increases by 0.1767 units. Numerically, this is not very large number, but long-run effects are often modest and still meaningful. Thus, magnitude of effect is small to moderate, but real and long-term.

4.5. Conducting diagnostic tests to confirm the validity of the research outcomes

This study applies diagnostic tests to improve the precision and reliability of the ARDL econometric model outcomes. Table 5 shows the different diagnostic tests. The Breusch-Godfrey Serial Correlation LM Test is applied to check for serial correlation. The results confirm that serial correlation is not detected, as the p-value of 0.2017 is higher than the 5% significance level. Likewise, the results from the Breusch-Pagan-Godfrey test for heteroscedasticity, which often occurs in time series data, show that no heteroscedasticity is present in this study, as the p-value of 0.1671 exceeds the 5% significance level.

The Regression Specification Error Test (RESET) is utilized to detect potential misspecifications in the approach. The analysis shows that the model specification is appropriate, with no errors or omitted variables, which ensures the reliability of the findings. This conclusion is supported by the p-value of 0.2383, which is greater than the 5% significance level.

Table 5. Diagnosis test outcomes: heteroscedasticity test, serial correlation LM test, Ramsey RESET test, CUSUM and CUSUMSQ test (prepared by authors, 2025)

Evaluate	P-value	Decision
Breusch-Godfrey Serial Correlation LM test	0.2017	No serial correlation
Breusch-Pagan-Godfrey test (Heteroscedasticity test)	0.1671	No heteroscedasticity exists
Ramsey Reset test	0.2383	The model is perfectly specified
CUSUM	–	Stable
CUSUMSQ	–	Stable

Figure 2 presents the results of the CUSUMSQ (Cumulative Sum of Squares) test, which is used to evaluate the stability of the ARDL model. The graph shows that the cumulative sum remains within the 5% significance boundaries, indicating that no structural breaks are present and that the model parameters remain stable throughout the study period. These results confirm the reliability and stability of the estimated relationships between AI, energy consumption, economic growth, and CO_2 emissions in Japan.

This study further examines the stability of the short-term beta coefficients in the ARDL model by applying the cumulative sum (CUSUM) and cumulative sum of squares (CUSUMSQ) tests to the recursive residuals.

Figure 3 presents the results of the CUSUM (Cumulative Sum) test, which is used to assess the stability of the ARDL model coefficients over time. The graph indicates that the cumulative sum remains within the 5% critical boundaries, confirming the absence of structural instability in the model during the study period. These findings support the overall stability and reliability of the estimated econometric model.

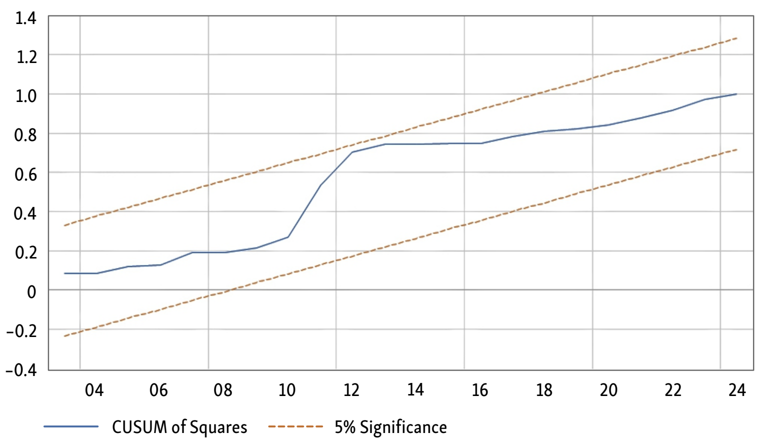

Figure 2. CUSUM of squares test results (prepared by authors, 2025)

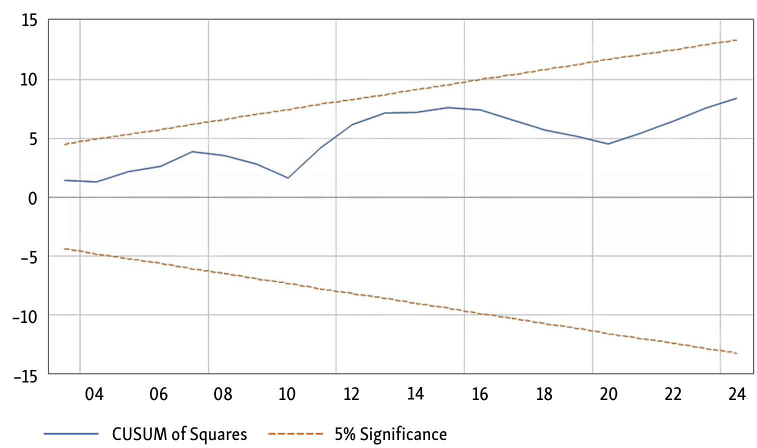

Figure 3. CUSUM test results (prepared by authors, 2025)

At the 5% significance level, the results of the CUSUM and CUSUMSQ tests findings suggest that no structural instability exists between the dependent and independent indicators. In this way tests confirm the stability of the model.

In discussion can be said that the findings of this present research using the ARDL econometric approach show that AI has a direct connection with carbon emission levels in Japan. Based on the literature analysis, AI is used in various sectors, and its progress depends on energy use. There are two directions of research results: one state that AI significantly reduces carbon emissions, when other – harm the environment and global warming. In turn, AI tools are utilizing around 50% of companies in developed country as Japan. The research results prove the positive relation between AI and carbon emissions. Hense, the results of the research confirm the first hypothesis: increasing AI adoption increases carbon emissions by increasing energy consumption. Analysis of research papers shows that energy use and CO_2 display a positive and meaningful impact on environmental quality in emerging countries, when in developed countries the impact is not clearly found. Energy use also increases emission levels, as AI and energy use are interlinked. As a result, emissions increase along with growth levels in Japan. The research found that energy consumption in Japan has a positive influence on carbon emissions, also confirming the second hypothesis, that higher energy use increases carbon emissions. When analyzing the literature on the topic of economic development it was highlighted that there is a connection between economic development and CO_2 emissions. In most cases of different emerging and developed countries when the economy grows, so does CO_2. The research results in this paper prove the third hypothesis when economic development is positively associated with rising carbon emissions. As indicated in the research paper, exports have an adverse relationship with carbon emissions, helping to enhance environmental sustainability in Japan. As well the research results show the same findings.

Policy implications and practical context. This research provides advanced insights into the field of environmental economics and contributes to environmental economics literature. Country's ability to cope with the economic and governance impacts of climate change depend largely on well-functioning political institutions. Therefore, the government should strive to foster a political climate. It is necessary to support decarbonization strategy and pursue relevant regulations to improve environmental quality.

The results of this research provide a basis for proposing several policy recommendations.

- The primary recommendation is that all countries should implement effective measures to reduce overall CO_2 emissions. This is especially important for developed economies. Such initiatives are essential to support sustainable economic growth.
- Policymakers should simultaneously consider Artificial Intelligence (AI), energy consumption, economic development, and CO_2 emissions in their decision-making, as the study identifies mutual causal interactions among these indicators.
- Economic expansion in most developed and emerging economies, coupled with the rapid growth of AI technologies, may lead to increased energy consumption.
- The analysis indicates that Japan, despite being a highly developed economy, continues to rely heavily on fossil fuels, which still dominate its national energy mix. Furthermore, approximately half of Japanese businesses have adopted generative AI technologies.

Nevertheless, a growing number of studies suggest that the rising use of AI may contribute to higher CO_2 emissions due to its intensive energy requirements. As AI-related energy consumption grows, decision-makers need to concentrate on decreasing dependence on fossil-based fuels while increasing the contribution of renewable energy, as this can contribute to a reduction in overall CO_2 emissions.

- It is also recommended to expand the legal and regulatory framework related to energy, AI, environmental, and economic recommendations by providing introduction of financial incentives and the development of technical assistance initiatives that promote sustainability and support national decarbonization strategies. Governments could also impose stricter environmental standards and regulations on high-emission industries to reduce environmental degradation and guide the selection of cleaner sources of energy. This is particularly important given the rapid expansion of AI technologies and rising energy consumption. The evidence generated by this study can guide policymakers in decision-making in designing targeted emission reduction policies intended for country-specific demands. These measures would help Japan steps seeking net-zero emissions while supporting sustainable economic development.
- The research results also provide practical insights for developing specific policy measures. Japan's "Green Growth Strategy for Carbon Neutrality by 2050" can be achieved more effectively by reducing fossil fuel dependency. Therefore, it is recommended that Japan accelerate its transition to renewable energy sources, as greater reliance on clean energy could mitigate the environmental impact of expanding AI adoption and contribute to lower overall CO_2 emissions. Investments in green artificial intelligence tools are suggested in addition.
- Since CO_2 emissions remain one of the world's most pressing environmental challenges, it is vital that all countries work collectively to ensure a sustainable future. Ultimately, all countries should actively contribute to the global economy by formulating specific strategies and ways to reach sustainable economic development goals.

5. Conclusions

This study examined the impact of Artificial Intelligence (AI), energy consumption, exports, and economic development on CO_2 emissions in the country of Japan, covering almost 30 years of data from 1995 to 2024. The key goal of the research is to examine how these chosen indicators affect environmental conditions of sustainability.

Literature analysis indicates that AI can decrease or increase CO_2. AI has a great possibility to strengthen organizational performance, but from the other hand, energy consumption can exacerbate environmental problems. Recent surveys indicate that AI is widely adopted across business sectors in Japan. Analysis of research papers indicates that the association between energy consumption and carbon emissions has a positive and statistically significant effect on the environment in emerging countries, when in developed countries the effect is not clearly found. Likewise, Japan's emission levels rise with increasing energy consumption, largely because AI systems demand significant energy resources for both development and performance. Although AI and energy use are interlinked, they also directly impact economic growth, as a country's growth depends on the performance of AI and the level of energy consumption. Both factors contribute to environmental damage in Japan. Likewise, economic growth also increases emission levels alongside national development. However, exports is an indicator that help support sustainability in Japan. There are two perspectives concerning the link among AI and carbon emissions. The first perspective, supported by some research works, suggests that AI contributes to improving sustainability. The second perspective argues that AI increases emission levels. Our research outcomes align with the second perspective. The reason behind this is that AI and energy use are interconnected, and as a result, economic growth depends on these factors, while environmental issues also arise.

This research employs the ARDL (Autoregressive Distributed Lag) econometric approach to evaluate the short-term and long-term influences of variables such as AI, energy consumption, exports, and economic development on CO_2 emissions in the country of Japan. The ARDL approach is used to estimate short-term dynamics and long-term relationships among these indicators. Before applying the ARDL approach, several key requirements should be satisfied. First, the indicators should be stationery. The Augmented Dickey-Fuller (ADF) unit root test confirmed stationarity for the indicators (AI, energy consumption, exports, and economic development) either at level or at first difference. Stationarity at level indicates that the data is stable with no trend, while the first difference implies stationarity in the changes of the data rather than its levels. The second condition is the existence of cointegration, indicating a long-term interconnection among the indicators. The ARDL bounds test confirmed cointegration, as the F-statistic went beyond the upper and lower critical limits, validating presence of a long-term association between the indicators. Following the fulfillment of these conditions, the ARDL approach was applied for further estimation. To ensure the robustness and robustness of the findings, several diagnostic tests were utilized. The Breusch-Godfrey test indicated that serial correlation was not detected, indicating that the approach is well-specified. The Breusch-Pagan-Godfrey test showed no signs of heteroscedasticity which supports the accuracy of the model's standard errors. The Ramsey RESET test verified that the model correctly captures the functional specification of association between variables. Lastly, the CUSUM and CUSUMSQ tests demonstrated the structural stability of the model over time and revealed no structural breaks.

The present research examined the long-term and short-term effect among indicators in the country of Japan. The study identifies carbon emissions as the key outcome variable, while the explanatory variables include artificial intelligence, energy use, and economic growth, with exports serving as a control variable. The research outcomes are presented in different stages. The first stage of the outcomes shows the stationarity and cointegration of the indicators. The econometric ARDL model technique was then used for further investigations. The second stage presents the long-term and short-term findings. The econometric ARDL research outcomes show that artificial intelligence, energy use, and economic development have a positive effect on CO_2 emissions growth, when exports have a negative impact on carbon emissions. The third stage involves the use of a number of diagnostic tests to strengthen the research outcomes. The Breusch-Godfrey serial correlation test confirmed that the model has no autocorrelation and constant error variance (so, the model errors are reliable, and the results are accurate. The Regression Specification Error Test (RESET) results show that the model is correctly specified, meaning it accurately represents the relationships between the variables. The fourth and final stage addresses model stability. The Cumulative Sum of Squares (CUSUMSQ) and Cumulative Sum (CUSUM) tests prove that the model is stable with no structural breaks.

The first question of the research was: what is the effect of artificial intelligence adoption on carbon emissions? Research findings show (table 4) that AI negatively impacts the environment, as it is directly linked to increased energy use and increased level of emissions. It supports the second perspective in literature review which argues that AI increases emission levels. As well it contributes to the second research question: how does energy consumption influence CO_2 emissions? As a research output answering to the third study question (how does economic development affect CO_2 emissions?), the development of the country's economy has a positive relation with CO_2, and it also negatively impacts the environment in Japan. This finding also supports the same statement in literature analysis. AI is rapidly contributing to various sectors, especially the production sector, leading to higher energy consumption. Based on the research findings, energy use has a positive influence on carbon emissions, damaging the environment, when exports – has a negative influence on CO_2 contributing by improving the environment. This research indicates that chosen variables are interconnected and affect each other.

According to the findings of this research, a number of significant policy recommendations can be formulated. Governments, particularly in developed economies, should take decisive action to degrease carbon emissions in pursuit of sustainable economic development. Policymakers need to consider artificial intelligence (AI), energy consumption, economic growth, and exports as interdependent factors, given the bidirectional causal relationships identified in this research. In Japan, despite being a highly advanced economy, the energy mix continues to be largely dependent on fossil fuels, while nearly half of Japanese enterprises have already adopted generative AI technologies. As AI systems demand substantial energy for their development and operation, their growing adoption may intensify energy consumption and associated emissions. Therefore, Japan should strengthen its transition toward renewable energy sources and invest in green AI solutions to mitigate these effects. Expanding the regulatory framework to include integrated energy, AI, economic, and environmental guidelines, complemented by financial support and technical advisory programs would further promote sustainability and accelerate progress toward carbon neutrality. Moreover, stricter environmental standards for high-emission industries are essential to guide cleaner energy choices and improve environmental quality. Ultimately, coordinated global efforts are needed, as reducing CO_2 emissions remains one of the most urgent environmental challenges. All Countries should support the global economy by formulating clear strategies and action plans toward achieving sustainable and inclusive economic development. The results of this study have significant implications for environmental strategies aimed at reducing carbon emissions.

Although, the research investigated the direct linear relationship between AI, energy use, and CO_2 emissions, several research limitations remain. First, while the paper models multiple impacts of AI, energy consumption, exports, and economic development as control variable, additional variables may be evaluated. For instance, the effect of AI on different categories of energy use and other types of pollution, green and fossil-based energy, trade integration, urbanization, and/or investment in the ICT sector – using linear and non-linear research models. Future research could also analyze the influence of AI on sulphur dioxide emissions, and other environmental indicators. Moreover, since this study was conducted at the national level in Japan, it is difficult to capture the effects of specific regulations at the subnational level. Future research could therefore be extended to more granular levels, such as provinces or cities.

Author contributions

The authors contributed to the elaboration of this research as next: Lidija Kraujalienė (25%), Atif Yaseen (25%), Saulius Kromalcas (25%), Helga Marija Kauzonė (25%).

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