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Artificial Intelligence, Financial Access, and the Path to Sustainable Development: Insights from G-7 Countries

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Abstract: Achieving sustainable development in advanced economies requires reconciling rapid technological progress with growing environmental constraints. This study examines whether artificial intelligence (AI) innovation can enhance environmental sustainability alongside economic growth in the G-7 countries over the period 1990–2019. Using the load capacity curve (LCC) framework and the load capacity factor (LCF) as a measure of ecological sustainability, the analysis integrates AI innovation, financial accessibility, globalization, urbanization, and income dynamics. This study contributes to the literature by providing the first evidence on the role of AI innovation in shaping environmental carrying capacity within the LCC framework for advanced economies. Panel autoregressive distributed lag estimates reveal strong support for the LCC hypothesis, indicating a nonlinear income–environment relationship. AI innovation and financial accessibility significantly improve the LCF, suggesting that technological progress and inclusive finance can promote sustainability through efficiency gains and cleaner production. In contrast, globalization and urbanization reduce environmental carrying capacity, particularly at higher levels of ecological pressure. These findings highlight the importance of AI-driven innovation and green finance in sustainability strategies, while underscoring the need for stronger environmental governance to manage globalization and urban expansion in advanced economies.

Keywords: artificial intelligence, sustainable development, load capacity factor, financial accessibility, G-7 economies

1. Introduction

1.1. Background of the study

Environmental sustainability has emerged as a central concern for advanced economies, as sustained economic expansion, intensive resource use, and rising emissions continue to place pressure on ecological systems. Despite significant progress in income growth and technological advancement, many developed countries face persistent environmental imbalances that threaten long-term sustainable development [1, 2]. Climate change remains one of the most critical global challenges, with increasing temperatures, extreme weather events, and biodiversity loss posing serious risks to economic and social stability [3, 4]. The urgency of this issue is particularly evident in high-income economies, where production and consumption patterns are closely linked to fossil fuel dependence and carbon-intensive activities [5]. Although international agreements and national policies have aimed to curb emissions and promote greener growth paths, environmental degradation continues to persist alongside economic progress [6]. This paradox highlights the need to reassess the drivers of environmental sustainability and to identify mechanisms capable of decoupling economic growth from ecological stress. In this context, emerging technologies and structural transformations are increasingly viewed as potential tools for reconciling development objectives with environmental constraints,

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warranting deeper empirical investigation into their role within advanced economic systems.

The relevance of this challenge is particularly pronounced in the context of the G-7 economies, which collectively account for a substantial share of global income, industrial output, and carbon emissions. Although these countries have made notable commitments toward environmental protection and green transitions, their economic scale and consumption intensity continue to exert considerable pressure on natural ecosystems [7, 8]. Historically, the G-7 nations have contributed a large proportion of cumulative global emissions, underscoring their responsibility in addressing environmental degradation and climate change [9]. Moreover, these economies are often regarded as global leaders in policy innovation, technological development, and institutional capacity, positioning them uniquely to influence international sustainability agendas [6]. However, evidence suggests that environmental damage has not been fully mitigated despite advances in green policies and cleaner production strategies, indicating that traditional growth-oriented approaches may be insufficient [5]. This dual role of the G-7—as both a major contributor to environmental stress and a potential driver of global sustainability solutions—makes it an important case for empirical analysis. Understanding how economic growth, structural factors, and emerging technologies interact with environmental carrying capacity in these countries is therefore essential for designing effective and scalable sustainable development policies.

Artificial intelligence (AI) can influence environmental sustainability through multiple, interrelated channels that shape how economic activity interacts with ecological constraints [10]. One important pathway is the efficiency channel, whereby AI-enabled optimization improves energy management, production processes, and logistics, reducing resource use and emissions per unit of output. A second pathway is technological substitution, as AI accelerates innovation and the diffusion of cleaner technologies by enhancing monitoring, data processing, and decision-making in both firms and public institutions [11]. At the same time, AI-driven productivity gains may activate a scale effect, expanding output and consumption as costs decline, which can intensify pressure on natural resources and ecosystems [10]. The overall environmental impact of AI therefore depends on the balance between efficiency- and innovation-led gains and scale-induced resource expansion. Within the LCC framework, this interaction determines whether technological progress enables economies to operate within ecological carrying capacity or contributes to environmental overshoot. Accordingly, examining AI through a carrying-capacity perspective provides a nuanced understanding of its role in shaping long-run environmental sustainability.

Rapid technological progress, particularly in AI, has introduced new opportunities and challenges for achieving sustainable development in advanced economies. AI refers to a broad set of technologies that enable machines and digital systems to perform tasks traditionally requiring human intelligence, including data processing, prediction, and automated decision-making [10, 11]. In recent years, AI-driven innovation has expanded rapidly across sectors such as energy, manufacturing, finance, and transportation, raising expectations about its potential to improve efficiency and reduce environmental pressures [12, 13]. Moreover, concerns have been raised regarding the energy-intensive nature of digital infrastructure and the possible rebound effects associated with technology-led growth [14]. Empirical evidence increasingly suggests that AI can contribute to environmental improvement by optimizing industrial processes, supporting cleaner production, and enhancing resource management [15, 16]. However, the environmental implications of AI remain context dependent and may vary across countries and stages of development [17]. For the G-7 economies, where AI adoption and digital transformation are advancing rapidly, understanding whether AI innovation supports or undermines environmental sustainability is critical for aligning technological progress with long-term sustainable development goals.

To evaluate environmental sustainability more comprehensively, recent studies have increasingly relied on the load capacity factor (LCF), which captures the balance between ecological demand and available biological capacity. Introduced by Siche et al. [18] and later applied empirically by Pata and Kartal [19], the LCF integrates the ecological footprint and biocapacity into a single indicator, providing a broader assessment of environmental conditions than conventional pollution-based measures do. A value of the LCF greater than one indicates ecological sustainability, whereas a value less than one indicates environmental stress and unsustainable resource use [20, 21]. Building on this concept, the load capacity curve (LCC) hypothesis extends the traditional income–environment relationship by allowing for a nonlinear association between economic growth and environmental carrying capacity [22]. Compared with the ecological footprint alone, LCF is particularly well suited for analyzing sustainability in high-income economies, where environmental pressures arise not only from emissions but also from consumption patterns and resource intensity [23]. Applying the LCC framework therefore enables a more nuanced understanding of how economic expansion and structural factors influence environmental sustainability in the G-7 countries.

In addition to economic growth, several structural and institutional factors play critical roles in shaping environmental sustainability in advanced economies. Financial accessibility influences environmental outcomes by affecting investment decisions, technology adoption, and consumption patterns, with prior evidence suggesting both environmentally beneficial and harmful effects depending on institutional quality and development stages [24–26]. Globalization further complicates this relationship by expanding trade, capital flows, and production networks, which can either facilitate technology transfer and efficiency gains or intensify resource exploitation and emissions [27–29]. Urbanization also remains a key determinant of environmental pressure, as rapid urban growth increases the demand for energy, transport, and infrastructure, often at the expense of ecological balance [30, 31]. These factors do not operate in isolation; rather, they interact with technological innovation and economic growth to influence environmental carrying capacity. Understanding their combined effects within the LCC framework is therefore essential for identifying pathways through which advanced economies can pursue sustainable development without exceeding ecological limits.

Despite substantial progress in the environmental economics literature, existing evidence remains fragmented in its ability to explain how advanced economies can reconcile technological progress with ecological limits. Much of the empirical work has emphasized outcome-based environmental indicators, offering limited insight into whether economic systems operate within their regenerative capacity over time [23]. As a result, the sustainability implications of structural transformation in high-income countries are often assessed without explicitly accounting for ecological thresholds and carrying capacity dynamics. In parallel, the emerging literature on AI has focused primarily on productivity, growth, or emission-related outcomes, leaving its broader role in shaping environmental resilience and sustainability largely unexplored [14, 17]. Moreover, advanced economies such as the G-7 are characterized by deep financial systems, high globalization intensity, and advanced urban structures, which may alter the environmental effectiveness of digital innovation compared with that of developing regions [32, 33]. The absence of empirical evidence that captures these structural asymmetries and distributional responses across different environmental states limits our understanding of whether AI-driven progress genuinely supports sustainable development. Addressing this shortcoming requires a framework that goes beyond average effects and conventional indicators to evaluate sustainability within the context of environmental carrying capacity in technologically advanced economies.

This study aims to examine whether AI-driven innovation supports sustainable development in advanced economies by influencing environmental carrying capacity. Focusing on the G-7 countries over the period 1990–2019, the effects of AI innovation, financial accessibility, globalization, urbanization, and economic growth on the LCF within the LCC framework are analyzed [22]. The use of the LCF as a proxy for environmental sustainability is particularly appropriate for advanced economies, as it captures both environmental pressure and ecological availability in a single indicator. Unlike emission-based measures, the LCF reflects whether economic activity remains within the regenerative capacity of natural systems. AI innovation is proxied by AI-related patent activity, which reflects technological advancement and knowledge creation in digital and automation-related fields. Although patent data may not fully capture adoption intensity, it provides a consistent and widely used indicator of innovation across countries and over time. To capture both long-term relationships and heterogeneous environmental responses, this study applies panel autoregressive distributed lag (ARDL) and panel quantile regression techniques [34, 35]. By moving beyond average effects, the analysis provides evidence on how the sustainability role of AI and related structural factors varies across different environmental states. The findings are intended to inform policies that seek to align technological advancement, financial systems, and economic growth with long-term environmental sustainability in high-income economies.

Despite the growing body of research on environmental sustainability and technological innovation, several gaps remain in the existing empirical literature. Most studies examining AI and environmental outcomes rely on pollution-based indicators such as CO_2 emissions or ecological footprint, which do not directly measure ecological regenerative capacity or whether economies operate within environmental limits. Empirical applications of the LCC framework are still limited, especially for advanced economies, where high income levels, financial depth, and global integration may produce different sustainability dynamics. In addition, prior work largely emphasizes average effects and gives limited attention to nonlinear and long-run relationships within a carrying-capacity perspective.

1.2. Research objectives

To address the limitations identified in the existing literature, a structured empirical framework is required that combines a carrying-capacity-based sustainability measure with a dynamic and nonlinear modeling approach. Such a design moves beyond pollution-only indicators and average-effect models and allows sustainability to be evaluated relative to ecological limits under technological and structural change. Guided by this framework, the study pursues the following objectives:

1) To evaluate environmental sustainability in the G-7 economies using the LCF within an environmental carrying capacity framework.
2) To examine how AI innovation, financial accessibility, globalization, urbanization, and economic growth are associated with environmental carrying capacity.
3) To test whether the income–environment relationship follows a nonlinear long-run pattern consistent with the LCC hypothesis using a panel ARDL approach.

1.3. Contribution of the study

This study makes several distinct contributions to the literature on technology-driven environmental sustainability. First, it advances the application of the LCC framework by introducing AI innovation as a key determinant of the LCF, thereby shifting the focus from pollution-based outcomes to sustainability measured relative to ecological carrying capacity. Second, by concentrating on the G-7 economies, the analysis provides evidence from innovation-frontier countries where AI development, financial depth, and institutional capacity are sufficiently advanced to shape long-run environmental outcomes, a context that has received limited attention in existing LCC-based studies. Third, the study jointly examines AI innovation and financial accessibility within a unified empirical framework, allowing an assessment of how technological progress and financial inclusion interact to influence environmental carrying capacity. By integrating these elements, the study offers new insights into the conditions under which technological advancement can support sustainable development in high-income economies.

2. Literature Review and Hypothesis Development

2.1. Economic growth and environmental quality

The relationship between economic growth and environmental sustainability remains unsettled when sustainability is evaluated through environmental carrying capacity measures. A substantial strand of empirical research reports that income expansion is frequently associated with declining environmental capacity, mainly because higher output levels intensify resource extraction and ecological pressure, thereby reducing the LCF [32, 36, 37]. This pattern appears across both developed and emerging economies, suggesting that rising income by itself does not guarantee ecological improvement [33, 38]. At the same time, another line of evidence points to a nonlinear pattern in which environmental performance initially worsens but later improves as economies undergo structural upgrading and efficiency-oriented transformation [39, 40]. Cross-country comparisons further indicate that the magnitude and even the direction of the growth effect depend on institutional quality, production structure, and technological progress, with some studies reporting weak or statistically insignificant links [41, 42]. Taken together, the literature indicates that growth effects are conditional rather than automatic, which makes it necessary to examine economic expansion within a framework that explicitly accounts for ecological limits and regenerative capacity.

2.2. Artificial intelligence and environmental quality

AI is increasingly recognized as a structural driver that can influence environmental sustainability through efficiency gains, process optimization, and improved decision systems. Much of the existing literature links AI-driven technologies with cleaner production, higher energy efficiency, and more precise resource allocation, suggesting that digital and automated systems can reduce environmental pressure when integrated into production and management practices [15, 16, 43, 44]. At the same time, the evidence is not uniformly positive. A parallel stream of research points to rising energy demand associated with data centers and digital infrastructure, indicating that the environmental footprint of AI expansion can offset part of its efficiency benefits [45]. Empirical results also show nonlinear and context-sensitive effects, where the sustainability contribution of AI varies with innovation intensity, institutional conditions, and regional development stages [17, 46]. This variation suggests that AI does not produce uniform environmental outcomes across settings. Taken together, prior studies support the potential of AI to improve environmental performance but also highlight important trade-offs and heterogeneity, underscoring the need for broader sustainability indicators and carrying-capacity-based frameworks when evaluating its long-run environmental effects.

2.3. Financial accessibility and environmental quality

Financial accessibility is widely regarded as an important determinant of environmental outcomes because it shapes investment choices, production structures, and consumption behavior. A large part of the literature shows that broader access to finance can promote technological upgrading and cleaner production by enabling firms to adopt energy-efficient technologies and environmentally oriented innovations [47, 48]. At the same time, expanded financial access can also amplify environmental pressure when credit growth supports carbon-intensive industries and consumption-led expansion [49, 50]. Empirical findings from both advanced and emerging economies reflect this dual effect, with several studies reporting that financial deepening is associated with weaker environmental performance where regulatory oversight and green financing mechanisms are limited [25, 26]. By contrast, stronger institutional frameworks and targeted environmental policies appear to moderate these adverse effects. Overall, prior evidence suggests that the environmental consequences of financial accessibility depend less on financial expansion itself and more on how financial resources are allocated. This conditional relationship makes it necessary to evaluate financial accessibility within a carrying-capacity perspective when assessing its role in sustainable development in advanced economies.

2.4. Globalization and environmental quality

Globalization is widely treated as a structural force influencing environmental sustainability through trade integration, capital mobility, and cross-border production systems. A substantial body of work links globalization with environmental improvement through technology transfer, efficiency gains, and the diffusion of cleaner production practices across countries [27, 28]. International integration can also raise regulatory standards and environmental awareness through multilateral cooperation. At the same time, another stream of evidence associates globalization with rising environmental pressure, driven by expanded industrial output, higher energy use, and the relocation of pollution-intensive activities in response to cost incentives [48, 49]. Empirical results across country groups show that outcomes depend heavily on regulatory strength and institutional quality. Even in advanced economies, the net effect remains uncertain, since efficiency gains are frequently offset by scale expansion and consumption growth. Taken together, the literature points to a conditional rather than uniform relationship. This makes it important to evaluate globalization using carrying-capacity-based sustainability indicators to determine whether global integration ultimately supports or weakens ecological balance in high-income economies.

2.5. Urbanization and environmental quality

Urbanization represents a major structural driver of environmental change through its influence on energy demand, land use, and consumption behavior. A large share of empirical research associates rapid urban growth with higher industrial intensity, expanded transport systems, and infrastructure development, all of which increase resource use and place stress on ecological systems [30, 31]. Evidence from densely populated regions further shows that unmanaged urban expansion can reduce environmental carrying capacity through deforestation, fossil fuel dependence, and habitat degradation [50]. At the same time, the literature does not point to a uniform effect. Under certain institutional and planning conditions, urban concentration has been linked with efficiency gains, cleaner technology adoption, and improved infrastructure provision, which can moderate environmental pressure. Cross-country studies therefore report heterogeneous outcomes, with the environmental effect of urbanization varying by development stage, regulatory quality, and urban planning strategy. The overall implication is that urbanization itself is not determinative; its sustainability impact depends on governance and policy design. This makes a carrying-capacity-based assessment particularly relevant when evaluating long-run sustainability effects in advanced economies.

2.6. Literature gap

Although environmental sustainability has been widely studied, important gaps persist in understanding how advanced economies reconcile technological progress with ecological limits. Most existing studies rely on pollution-based indicators, offering limited insight into whether economic systems remain within their environmental carrying capacity. The evidence on the LCC hypothesis remains sparse and fragmented, particularly for high-income economies. Moreover, while AI has been increasingly examined in relation to growth and emissions, its role in shaping environmental carrying capacity and sustainable development in technologically advanced, highly globalized economies is largely unexplored. Prior research has also tended to focus on average effects, overlooking heterogeneity in environmental responses across different sustainability states. These limitations hinder a clear assessment of whether AI-driven innovation and structural factors genuinely support sustainable development in advanced economies, underscoring the need for an integrated and distribution-sensitive analytical framework.

2.7. Hypothesis development

The preceding review indicates that the relationships between economic growth, AI, financial accessibility, globalization, urbanization, and environmental sustainability are complex and conditional rather than automatic. Since this study evaluates sustainability using a carrying-capacity-based indicator, the direction and magnitude of these determinants must be examined in terms of their influence on ecological balance and regenerative capacity. Prior empirical evidence highlights heterogeneous outcomes across institutional and structural contexts, suggesting that the sustainability impact of these macroeconomic and technological drivers depends on policy design, innovation intensity, and resource allocation mechanisms. Based on this theoretical and empirical foundation, the following hypotheses are formulated. Figure 1 shows the hypothesis development of the study.

Economic growth may exert pressure on environmental carrying capacity through scale expansion, higher resource extraction, and increased production intensity. However, structural transformation, technological upgrading, and efficiency improvements in advanced economies may partially offset these adverse effects. Therefore, the growth–environment relationship is expected to be significant but potentially nonlinear and context dependent.

H1: Economic growth significantly influences environmental carrying capacity.

AI can improve environmental performance through optimization, efficiency gains, and cleaner production processes. At the same time, digital infrastructure expansion and rising electricity demand may generate offsetting environmental pressures. The overall effect is therefore expected to be significant but dependent on the balance between technological efficiency and energy consumption.

H2: AI development significantly influences environmental carrying capacity.

Financial accessibility shapes environmental outcomes through capital allocation decisions. Access to finance may promote green innovation and energy-efficient technologies, yet it may also stimulate environmentally intensive production and consumption if regulatory oversight is weak. Accordingly, its sustainability impact is expected to be significant and conditional on resource allocation patterns.

H3: Financial accessibility significantly influences environmental carrying capacity.

Globalization affects environmental quality through trade integration, capital mobility, and technology diffusion. While global integration can enhance efficiency and regulatory convergence, scale effects and production relocation may intensify ecological pressure. The net outcome is therefore expected to be significant but dependent on institutional and regulatory conditions.

H4: Globalization significantly influences environmental carrying capacity.

Urbanization influences sustainability through its effects on energy demand, infrastructure development, and land use patterns. Rapid and unmanaged urban expansion may reduce ecological capacity, whereas planned urban concentration can generate efficiency gains and technological improvements. Thus, the environmental effect of urbanization is expected to be significant and governance dependent.

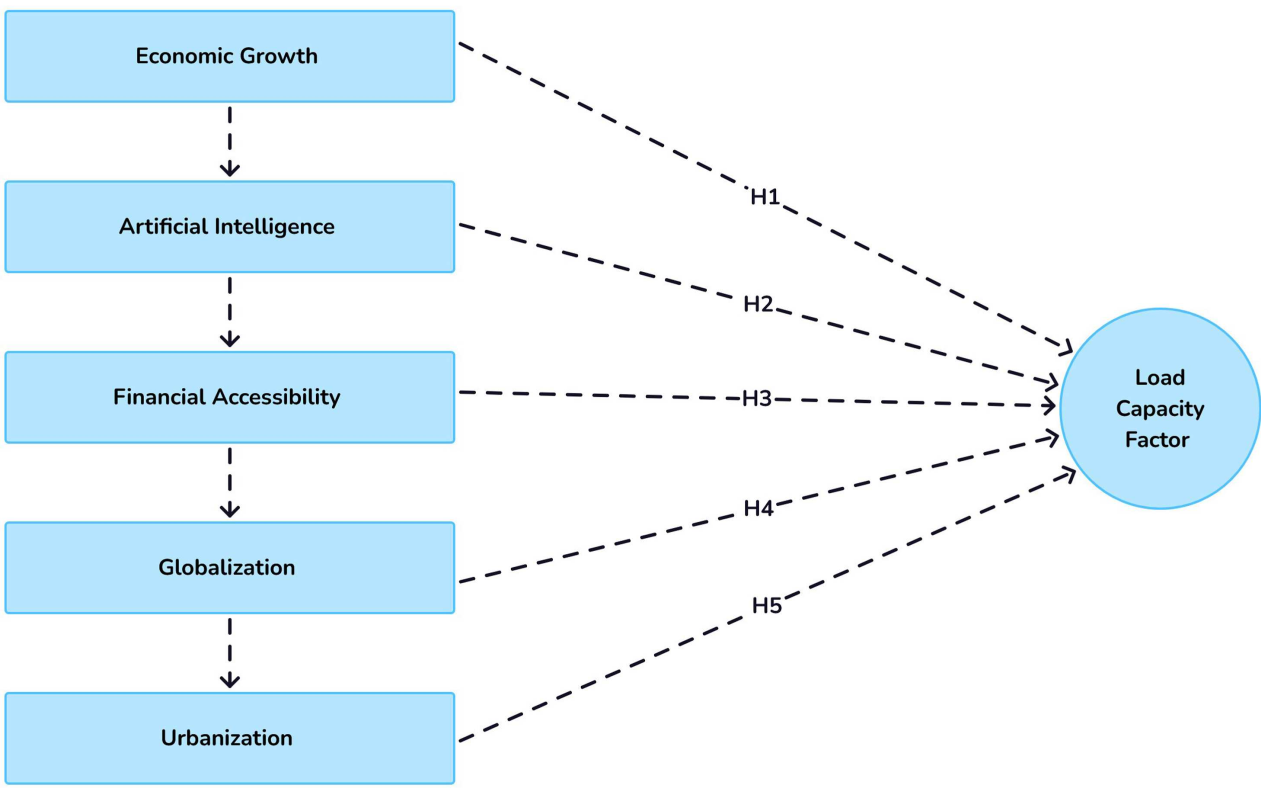
H5: Urbanization significantly influences environmental carrying capacity.

3. Methodology

3.1. Data and variables

This study uses an annual panel dataset for the G-7 economies spanning 1990–2019. Environmental sustainability is proxied by the LCF obtained from the Global Footprint Network, which reflects the balance between ecological demand and biocapacity. Economic growth is measured by gross domestic product

Figure 1
Hypothesis development of the study



and its squared term, sourced from the World Development Indicators, to capture potential nonlinear dynamics under the LCC framework. AI innovation is represented by AI-related patent activity collected from our world in data. AI innovation is proxied using AI-related patent activity, reflecting the development of codified technological knowledge and inventive effort. Patent indicators are frequently adopted in cross-country research because they offer a consistent and internationally comparable measure of technological advancement, particularly in high-income economies where patenting is closely associated with research and development outcomes. In the case of AI, patent activity captures progress in algorithmic design and computational techniques that support productivity improvements and technological upgrading. Although patent counts do not directly reflect the extent of technology adoption or diffusion, they provide a reliable indication of innovation capacity in long-run empirical analyses. This limitation is acknowledged and does not compromise the validity of the proxy for the objectives of the present study. Financial accessibility is measured via indicators of access to formal financial services drawn from the Global Financial Inclusion database. Globalization is captured through a composite globalization index obtained from the KOF Globalization Index, whereas urbanization is measured as the share of the urban population in the total population from the World Development Indicators. All variables are expressed in natural logarithms to ensure scale consistency and mitigate heteroskedasticity.

3.2. Theoretical framework

In the rapidly expanding G-7 nations, the LCF is a dependent variable used to capture the pertinent components of environmental quality. Siche et al. [18] were the first to mention the LCF in the literature, and Pata and Kartal [19] were the first to conduct empirical research on the factors influencing the LCF. The LCF indicator, which takes into account both man-made environmental pressures and opportunities for ecological provision, is the foundation of LCC theory [22]. A higher LCF is indicative of a healthier environment since the LCF incorporates both Ecological Footprint (EF) and biocapacity in the denominator. By comparing the ecological footprint and biological resources, LCFs provide a more comprehensive examination of the environment [23]. Although both the environmental Kuznets curve (EKC) and the LCC frameworks use nonlinear income terms, they differ in purpose and interpretation. EKC analyses focus on environmental degradation, such as emissions, and examine whether pollution declines beyond a certain income level. In contrast, the LCC framework evaluates sustainability relative to ecological carrying capacity, using indicators that compare environmental demand with biocapacity. In this study, sustainability is measured by the LCF, which reflects whether economic activity remains within ecological limits. Therefore, the inclusion of income and its squared term captures nonlinearities in environmental carrying capacity rather than conventional EKC-type pollution dynamics.

To improve the understanding of this study, we created the following Equation (1) for LCC theory:

$$Load\ Capacity\ Factor = f\left(GDP,\ GDP^2,\ K_t\right) \tag{1}$$

In Equation (1), the variables for economic growth are GDP and GDP^2, whereas the variable for other factors influencing the LCF is K_t. Equation (2) seeks to provide an expanded view of the elements changing the LCF by including additional relevant variables such as globalization, urbanization, financial accessibility, innovation in AI, and economic growth.

$$LCF = f\left(GDP,\ GDP^2, AI, FA, GOB,\ URBA\right) \tag{2}$$

The load capacity factor (LCF), economic growth (GDP), artificial intelligence (AI) innovation, financial accessibility (FA), globalization (GOB), and urbanization (URBA) are the abbreviations used in Equation (2). The economic explanation of this equation can be obtained via Equation (3).

$$\begin{aligned} LCF_{it} &= \partial_0 + \partial_1 GDP_{it} + \partial_2 GDP_{it}^2 + \partial_3 AI_{it} + \partial_4 FA_{it} \\ &\quad + \partial_5 GOB_{it} + \partial_6 URBA_{it} \end{aligned} \tag{3}$$

In Equation (4), the variables' logarithmic values are demonstrated. It increases understanding and enables the formulation of implications on the basis of statistics by breaking down complex intersections into simpler linear forms. The logarithmic scale allows for data of different dimensions and aids in alleviating heteroscedasticity when broad ranges need to be reduced.

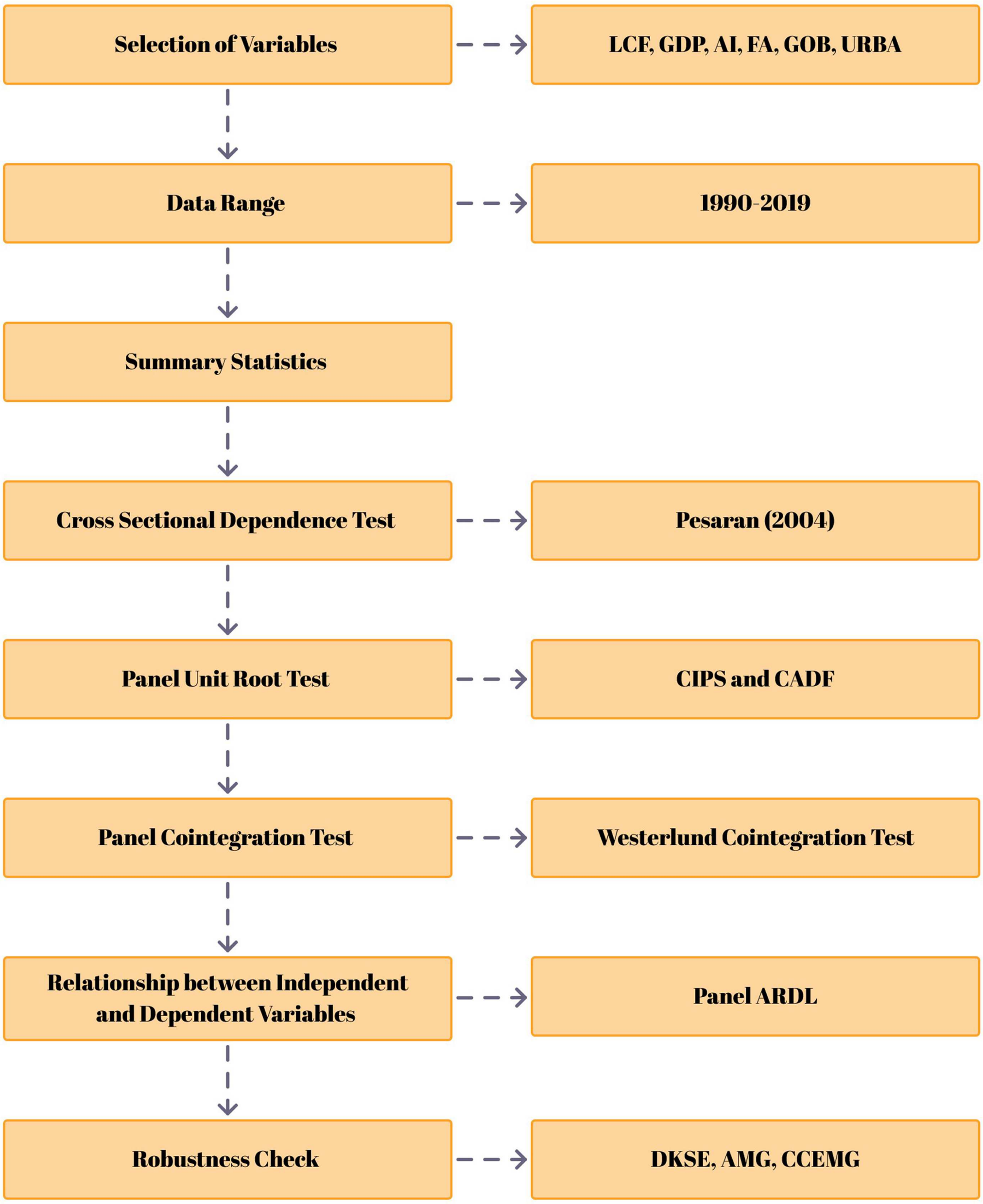
$$\begin{aligned} LLCF_{it} &= \partial_0 + \partial_1 LGDP_{it} + \partial_2 LGDP_{it}^2 + \partial_3 LAI_{it} + \partial_4 LFA_{it} \\ &\quad + \partial_5 LGOB_{it} + \partial_6 LURBA_{it} \end{aligned} \tag{4}$$

The empirical model relates environmental sustainability, measured by the LCF, to economic activity and structural drivers within the LCC framework. Income and its squared term are included to capture potential nonlinearities in environmental carrying capacity as economies expand. AI innovation and financial accessibility are expected to enhance sustainability by improving efficiency and supporting cleaner production, while globalization and urbanization may exert additional pressure on ecological capacity through scale and consumption effects. In this way, the econometric specification operationalizes the LCC framework by examining whether economic growth and structural factors allow economies to remain within ecological limits in the long run, while the error-correction structure captures short-run adjustments toward this equilibrium.

3.3. Empirical strategy

The empirical analysis follows a structured estimation strategy to ensure robust and reliable inference. The analysis begins by testing for cross-sectional dependence using Pesaran's CD test, reflecting the high degree of economic integration and common shocks among the G-7 economies. Slope heterogeneity is subsequently examined to assess whether the estimated relationships vary across countries. To determine the time-series properties of the variables under these conditions, second-generation panel unit root tests, namely, Cross-sectionally augmented m, Pesaran, and Shin (CIPS) panel unit root test and Cross-sectionally Augmented Dickey-Fuller (CADF), are employed, as they explicitly account for cross-sectional dependence and heterogeneity. After establishing stationarity, long-run relationships among the variables are tested using the Westerlund panel cointegration approach. Given evidence of cointegration, the study applies a panel ARDL model under the pooled mean group framework to estimate both long-run equilibrium relationships and short-run adjustment dynamics. To ensure the robustness of the long-run findings, alternative estimators are employed, including Driscoll–Kraay standard errors (DKSE), the augmented mean group (AMG) estimator, and the common correlated effects mean group (CCEMG) estimator. Figure 2 presents a schematic overview of the empirical estimation procedure.

Figure 2
Flow of estimation approach



4. Results and Discussion

The descriptive statistics in Table 1 summarize the distributional characteristics of the variables across the G-7 economies. The LCF exhibits a negative average value, which does not imply negative sustainability per se, but rather indicates that, on average, ecological demand exceeded biocapacity during the sample period, reflecting persistent pressure on environmental carrying capacity. Economic growth variables display relatively low dispersion, consistent with the stable and mature income structures of advanced economies. AI innovation and financial accessibility show moderate variation, highlighting cross-country differences in technological capability and financial depth despite broadly similar development levels. By contrast, globalization and urbanization exhibit limited variability, which is in line with the highly integrated and urbanized nature of the G-7 economies.

Table 1
Descriptive statistics

Variable	Mean	Std. dev.	Min	Max
LLCF	–0.913	0.812	–2.012	0.764
LGDP	10.684	0.189	10.342	11.264
$LGDP^2$	114.103	3.918	106.752	126.847
LAI	5.612	1.984	1.721	9.643
LFA	4.892	0.364	4.412	5.942
LGOB	4.438	0.057	4.312	4.501
LURBA	4.389	0.078	4.231	4.529

The results of the cross-sectional dependence test, reported in Table 2, indicate statistically significant cross-sectional dependence across all the variables. This finding suggests that the

Table 2
Cross-sectional dependence test

Variable	CD statistic	*p* value
LLCF	5.912	0.000
LGDP	5.428	0.000
$LGDP^2$	5.401	0.000
LAI	13.118	0.000
LFA	4.102	0.002
LGOB	11.287	0.000
LURBA	16.438	0.000

G-7 economies are interconnected through common shocks, shared technological trends, and global economic integration. Ignoring such dependence could lead to biased and inconsistent estimates in conventional panel models. Therefore, the presence of cross-sectional dependence justifies the use of second-generation panel techniques and advanced estimators that explicitly account for interdependencies among countries in subsequent analyses.

The results of the second-generation unit root tests, reported in Table 3, indicate mixed orders of integration across the variables when cross-sectional dependence is taken into account. The CIPS and CADF statistics confirm that the LCF, economic growth, and urbanization variables are nonstationary at levels but become stationary after first differencing, whereas AI, financial accessibility, and globalization are stationary at level. These findings satisfy the requirement of mixed integration orders and justify the application of the panel ARDL approach, which allows variables integrated of order I(0) and I(1) but not I(2).

The cointegration test results reported in the modified statistics table indicate the presence of a long-run equilibrium relationship among the variables. The significant values of the panel-based statistics (Gt and Ga) suggest that the null hypothesis of no cointegration can be rejected in favor of a long-term association (Table 4). In particular, the statistically significant Pt statistic provides strong evidence of cointegration, confirming that the variables move together over time despite short-run fluctuations. Although the Pa statistic remains insignificant, panel cointegration inference relies on joint evidence rather than a single statistic. Overall, these results support the existence of a stable long-run relationship, justifying the subsequent estimation of long-run and short-run dynamics via panel ARDL techniques.

The panel ARDL estimates reveal a clear nonlinear relationship between economic growth and environmental sustainability, measured by the LCF. In the long run, the coefficient on economic growth (LGDP = −0.052) is negative and statistically significant, indicating that income expansion initially places pressure on environmental carrying capacity through intensified resource use and ecological demand. In contrast, the positive and significant coefficient of the squared income term ($LGDP^2$ = 0.074) provides strong support for the LCC hypothesis, suggesting that beyond a certain income threshold, further growth contributes to improved environmental sustainability, likely driven by technological upgrading, efficiency gains, and structural transformation. This nonlinear pattern is consistent with prior studies documenting growth–environment dynamics within the LCF framework [23, 36, 37]. In the short run, the coefficient of ΔLGDP remains negative, implying that growth-related shocks tend to exacerbate environmental stress during the adjustment phase. However, the short-run effect of $\Delta LGDP^2$ reflects transitional dynamics rather than a sustained improvement in environmental capacity and should therefore be interpreted with caution. Taken together, the estimated coefficients imply a turning point at which the effect of economic growth on environmental sustainability shifts from exerting pressure on ecological capacity to supporting improvements in carrying capacity.

The panel ARDL estimates suggest that AI innovation contributes positively to environmental sustainability in the G-7 economies. In the long run, the positive and statistically significant coefficient of AI innovation (LAI = 0.156) indicates that AI-driven technological progress enhances the LCF by improving production efficiency, facilitating cleaner technologies, and strengthening resource management. This finding is consistent with earlier studies highlighting the role of digital intelligence and

Table 3
Second-generation unit root test results

Variables	CIPS		CADF		Decision
	I(0)	I(1)	I(0)	I(1)	
LLCF	–0.712	–3.942***	–1.284	–3.718***	I(1)
LGDP	–1.764	–3.428***	–1.512	–3.769***	I(1)
$LGDP^2$	–1.936	–3.556**	–1.589	–3.621***	I(1)
LAI	–2.947**	–4.702***	–3.081**	–3.904***	I(0)
LFA	–1.152	–3.618***	–3.042**	–3.861***	I(0)
LGOB	–3.154**	–5.517***	–1.586	–3.533***	I(0)
LURBA	–0.704	–3.917***	–0.936	–3.154**	I(1)

***: Significant at 1% level **: Significant at 5% level *: significant at 10% level

Table 4
Westerlund cointegration test

Statistics	Value	*z* value	*p* value
Gt	–1.6124	–0.3821	0.0287
Ga	–2.7419	1.2456	0.0124
Pt	–4.1386	–1.5294	0.0419
Pa	–2.6853	–0.2148	0.2916

automation in reducing environmental pressure through optimization and technological upgrading [15–17]. In the short run, the coefficient of ΔLAI remains positive but smaller in magnitude, implying that the immediate sustainability gains from AI adoption are modest and largely reflect short-term efficiency improvements rather than deep structural changes. Taken together, these results indicate that while AI can deliver limited environmental benefits in the adjustment phase, its contribution to environmental sustainability becomes more substantial over time as technological innovation is integrated into economic structures and production systems.

Access to finance emerges as an important structural factor influencing environmental sustainability in the G-7 economies. The long-run ARDL estimates show a positive and statistically significant association between financial accessibility and the LCF (LFA = 0.821), indicating that broader access to financial resources supports environmental carrying capacity by enabling investment in cleaner technologies, energy-efficient production, and environmentally friendly innovation. This finding aligns with earlier research emphasizing that well-developed financial systems can foster sustainable development when credit is directed toward productive and green activities [25, 26]. In the short run, the coefficient of ΔLFA remains positive but modest in magnitude, suggesting that improvements in financial access translate into limited immediate sustainability gains. Such short-run effects likely reflect adjustment costs and time lags, as financial expansion initially stimulates economic activity before contributing to measurable improvements in environmental capacity. Overall, the results indicate that the sustainability benefits of financial accessibility are realized mainly over the long term, underscoring the role of sustained green finance in supporting ecological capacity.

Greater global integration appears to pose challenges for environmental sustainability in the G-7 economies. The long-run ARDL estimates show a negative and statistically significant coefficient for globalization (LGOB = −1.764), indicating that increased openness is associated with a decline in the LCF. This result suggests that, in advanced economies, the scale effects of globalization, including expanded production, higher trade-related energy use, and intensified resource extraction, may outweigh potential efficiency gains and thereby place pressure on environmental carrying capacity. This finding is consistent with previous studies documenting adverse environmental effects of globalization in high-income contexts [27, 29]. In the short run, the coefficient of ΔLGOB also remains negative, although smaller in magnitude, implying that globalization-related shocks tend to generate immediate environmental stress during the adjustment phase. These short-term effects reflect rapid increases in trade activity and production intensity before regulatory or technological responses can offset ecological pressures (Table 5). Differences in coefficient magnitudes and, in some cases, signs across alternative estimators reflect cross-country heterogeneity and the influence of unobserved common factors, while the overall long-run relationship remains consistent with the baseline results. Figure 3 shows how different explanatory variables impact LCF.

The robustness results reported in Table 6 confirm the consistency and reliability of the baseline findings. Across the DKSE, AMG, and CCEMG estimators, the signs and significance of the key variables remain largely unchanged (Table 6). Economic growth continues to exhibit a nonlinear relationship with the LCF, whereas AI and financial accessibility consistently enhance environmental sustainability. In contrast, globalization and urbanization retain their negative effects on environmental carrying capacity across alternative estimators. The stability of these results across models that explicitly account for cross-sectional dependence and unobserved common factors strengthens confidence in the main conclusions and suggests that the estimated relationships are not sensitive to estimator choice.

5. Summary of Key Empirical Findings

The main empirical findings of the study can be summarized as follows. First, economic growth exhibits a statistically significant nonlinear relationship with environmental sustainability, confirming the LCC hypothesis for the G-7 economies. While income growth initially reduces environmental carrying capacity, further growth beyond a certain threshold contributes to ecological improvement.

Second, AI innovation has a positive and statistically significant effect on the LCF in both the short and long run, indicating

Table 5
Panel ARDL results

Variable	Coefficient	Std. error	t-Stat	p value
Long-run estimation				
LGDP	–0.052	0.0312	–1.667	0.0412
LGDP^2	0.074	0.0715	1.035	0.0496
LAI	0.156	0.0884	1.764	0.0189
LFA	0.821	0.0621	2.412	0.0197
LGOB	–1.764	0.1126	–1.567	0.0338
LURBA	–0.051	0.0249	–2.049	0.0441
Short-run estimation				
COINTEQ01	–0.043	0.1724	–2.494	0.0314
D(LGDP)	–0.039	0.0061	–1.623	0.0832
D(LGDP^2)	0.114	0.0617	1.847	0.0285
D(LAI)	0.033	0.0526	2.628	0.0091
D(LFA)	0.097	0.9113	0.106	0.0216
D(LGOB)	–0.642	1.1984	–0.536	0.0918
D(LURBA)	–0.205	0.4512	–0.454	0.0639

Figure 3
Impact of explanatory variables on LCF

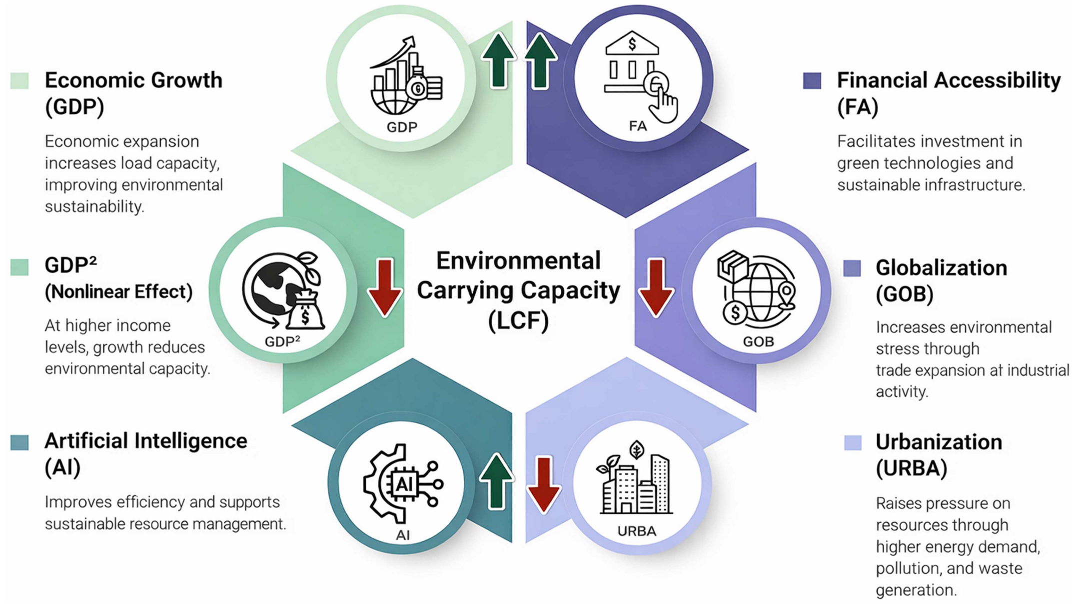


Table 6
Robustness check

Variables	DKSE	AMG	CCEMG
LGDP	–0.118***	–0.053**	–0.061***
	(0.0112)	(0.0281)	(0.0764)
$LGDP^2$	0.026***	0.071*	0.187***
	(0.0124)	(0.1186)	(0.0498)
LAI	0.00921***	0.0524***	0.0156***
	(0.0231)	(0.0619)	(0.198)
LFA	0.301***	0.512**	0.702**
	(0.011)	(0.0492)	(3.814)
LGOB	–0.884***	–0.598*	0.391**
	(0.0576)	(0.823)	(0.241)
LURBA	–0.487***	–0.942*	–0.521**
	(1.216)	(11.32)	(42.85)
Constant	19.864**	16.982**	12.417**
	(0.2914)	(0.5483)	(0.9031)
Observations	91	91	91
Number of groups	7	7	7

Note: CCEMG standard errors are larger due to cross-sectional dependence correction and slope heterogeneity and should be interpreted as conservative estimates.
***: Significant at 1% level **: Significant at 5% level *: significant at 10% level

that AI-driven technological progress enhances environmental sustainability through efficiency gains and improved resource management. Third, financial accessibility positively influences environmental carrying capacity in the long run, suggesting that well-functioning financial systems support sustainable investment and cleaner production when aligned with advanced institutional frameworks.

Fourth, globalization exerts a negative and statistically significant impact on environmental sustainability, reflecting scale effects and increased resource use associated with global economic integration. Finally, urbanization is found to reduce environmental carrying capacity in both the short and long run, highlighting the persistent ecological pressures arising from high urban concentration in advanced economies.

6. Conclusion and Policy Implications

6.1. Conclusion

This study contributes to the literature by providing new empirical evidence on the role of AI in shaping environmental sustainability within an environmental carrying capacity framework. By employing the LCF rather than conventional pollution-based indicators, the analysis offers a broader assessment of sustainability that explicitly accounts for ecological limits. Moreover, the study extends the LCC hypothesis to include AI, financial accessibility, globalization, and urbanization in the context of advanced economies. The use of panel ARDL techniques, complemented by robustness checks that account for cross-sectional dependence and heterogeneity, further enhances the methodological rigor of the findings.

6.2. Policy implications

The findings imply differentiated policy priorities across the G-7 economies. For the United States and Canada, policies should focus on integrating AI into energy systems, transport, and manufacturing to improve efficiency while tightening environmental standards to offset globalization-driven scale effects. In Germany, France, and Italy, where industrial restructuring and urban density are prominent, AI-enabled green manufacturing, smart urban infrastructure, and targeted financial incentives for low-carbon innovation can help enhance environmental carrying capacity. Japan should prioritize AI-driven energy efficiency and circular economy solutions to address resource constraints and urban pressures while leveraging advanced digital technologies to reduce energy intensity. In the United Kingdom, strengthening green finance mechanisms and directing financial accessibility toward sustainable investments can amplify the positive long-term environmental effects identified in the analysis. Across all the G-7 countries, globalization-related environmental pressures call for coordinated green trade policies, carbon border measures, and international standards that encourage cleaner production. Moreover, sustainable urban planning—supported by AI-based smart city technologies—can mitigate the adverse environmental impacts of urbanization. Overall, aligning AI innovation, financial systems, and country-specific structural characteristics with environmental objectives is essential for improving environmental carrying capacity and achieving long-term sustainable development in the G-7 region.

7. Limitations and Future Research Directions

Despite its contributions, this study has several limitations. First, the analysis is restricted to the G-7 economies, which may limit the generalizability of the findings to developing or emerging countries. Second, AI is proxied by patent-based measures, which may not fully capture actual AI adoption or application intensity. Future research could extend the analysis to broader country groups, incorporate alternative AI indicators, and explore sector-specific effects. Additionally, examining the interaction between AI, environmental regulation, and renewable energy adoption could provide deeper insights into sustainable development pathways.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are publicly available from the following sources:

1) Load Capacity Factor (LCF): Global Footprint Network – https://data.footprintnetwork.org
2) Economic Growth (GDP) and Urbanization: World Bank, World Development Indicators (WDI) – https://databank.worldbank.org/source/world-development-indicators
3) Artificial Intelligence (AI) Patent Data: Our World in Data – https://ourworldindata.org
4) Financial Accessibility: Global Financial Inclusion (Global Findex) Database, World Bank – https://globalfindex.worldbank.org
5) Globalization Index: KOF Swiss Economic Institute – https://kof.ethz.ch/en/forecasts-and-indicators/indicators/kof-globalisation-index.html

All datasets are openly accessible and do not require special permission for academic use.

Author Contribution Statement

Mohammad Ridwan: Conceptualization, Methodology, Software, Investigation, Writing – review & editing. **Kabaly P Subramanian:** Conceptualization, Software, Validation, Resources, Writing – original draft, Writing – review & editing. **Jaheer Mukthar K.P.:** Conceptualization, Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Supervision, Project administration. **Binata Rani Sen:** Conceptualization, Methodology, Investigation, Writing – original draft, Writing – review & editing. **Minghui Jiang:** Conceptualization, Formal analysis, Writing – review & editing, Visualization. **Mujeeb Saif Mohsen Al Absy:** Investigation, Resources, Data curation, Writing – review & editing.

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