# Green Innovation, Agro-Environmental and Energy Intensity: Evidence from Emerging Economies

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**Abstract.** This paper investigates the dynamic responses of green technology innovation and agriculture environmental efficiency on energy intensity in Emerging and Growth-Leading Economies. This study use the Dynamic Common Correlated Effect to evaluate cross-sectional dependence among cross-sectional units and to allow heterogeneous coefficients in a panel. Panel estimation shows that energy intensity is reduced in response to the introduction of more energy-efficient technology. It is also worth noting that rising and growth-leading economies have been able to become more energy efficient as a result of boosting agricultural production's environmental performance and spending more on R&D. The outcomes from this study provide a sense of direction for policymaker and future researchers for future studies in this domain.

**Keywords:** Green Technology Innovation · Energy Intensity · Emerging and Growth-Leading Economies · Dynamic Common Correlated Effect

## 1 Introduction

The Sustainable Development Goals 7 specifically aims to improve the access to affordable, reliable, sustainable, and modern energy. One of the underpinned targets under SDG 7 is to improve the energy efficiency and the goals are inextricably connected to significant reductions in air pollution. Indeed, energy is agreed by many as the source of growth. As economies grow, energy consumption increases. However, over the last three decades, rapid increases in energy consumption and economic growth have been cited as the driving force behind escalating environmental degradation, which continues to pose a threat to people and the environment [2]. Hence, the aims to foster economic growth in countries with least amount of environmental harm is now a top priority.

Today, every country in the globe is concerned about energy difficulties and global warming, as well as solutions to both problems. This is especially true in the case of emerging economies, because emerging economies experiences the biggest growth in energy demand. Is it expected that in the period 2005 to 2030, the emerging economies


A. Asmawi (Ed.): ICTIM 2022, AEBMR 228, pp. 18–30, 2022.
https://doi.org/10.2991/978-94-6463-080-0_3

will become the world's top carbon emitters and energy demand in China and India is expected to account for 45% of the increase in world energy demand [25].

Modelling the link between energy intensity and income has been a very active area of research (see [25]; [6]; [16]) and confirmed the significant effect of income on energy intensity. Meanwhile, according to [19] energy intensity may decrease with economic growth due to improvement in technology. In fact, technology innovation, particularly green technology innovation, is a critical tool for resolving the internal conflict between economic expansion and pollution, and it has emerged as a crucial factor in fostering green and energy efficiency [4]. Green technology has grown in popularity in recent years. Conspicuously, most of the researcher start to observe and analyses the ecological effect of coal burning of manufacturing and industrial plants where it can reduce their negative environmental consequences by conversion production process to produce less or waste by the products in the early 19th century [20].

The "win-win" target of energy efficiency-growth not only depends on the technology innovation but also the economics sector role in promoting low energy intensity. To put it another way, energy efficient practices in economic sector such as agriculture and industrial sector is essential to minimising the environmental negative consequences. This sector requires further attention not only because of the potential of energy efficiency but also the potential ground for the development of green technology innovation.

However, given the green technology in meeting future energy needs and achieving the SDGs, it is surprising that so little research has been done on modelling the relationship between green technology and energy intensity. Hence, this study contributes to literature fundamentally in two folds. Firstly, to date, many studies have mainly focused on the contribution human material products (generally proxy by GDP) to energy consumption and vice versa, however, less consideration on the role of technological innovation on energy consumption. Although, empirical evidence such as [17] and [21] demonstrate that improving technical innovation capability can improve energy efficiency and lower energy consumption intensity, the pure technological innovation ignores the environment's external effects. According to [30] innovation in green technology is more in line with the goal of sustainable development but rarely used as the determinant of energy consumption intensity.

Secondly, the most common indicator for energy intensity are the two different economic levels, namely economics sector, and Gross Domestic Product (GDP) [26]. Sectoral production is now more compelled than ever to embrace sustainability. In recent study by [32], it shows that agriculture sector has not played a significant role yet in promoting low energy intensity in middle income countries. However, the study only empirical examine the sectoral contribution and not specifically consider the environmental initiative in agriculture sector. Hence, this study adopted the environmental performance of the agricultural production indicator to re-examine the role played by agriculture sector in embrace sustainability.

At this juncture, this study aims to is to investigate the effects of green technology innovations and agricultural environmental efficiency on energy use. In order to achieve this aim, this study will focus the emerging economies. Without doubt, the emerging economies will determine the growth prospects of the world economy in the next decade. This is due to the fact that these countries have implemented acceptable growth strategies, such as developing national R&D activities, and utilising advanced technology widely [28]. As a result, it is critical to verify whether these countries have exhibited progress on green growth particularly in energy efficiency.

The paper is organized as follows. Next section will present a clear review of the existing literature. Section 3 will be explained describes the methodology. Section 4 presents the empirical result and finally Sect. 5 will draw a conclusion.

## 2 Literature Review

Energy intensity has been considered as one of the major indicators that measure energy efficiency. The increase of energy efficiency would have a positive impact to the environment. Besides that, the excessive consumption of non-renewable energy such as fossil fuel would lead to the increase of carbon emissions that calls for an immediate solution. Hence, many countries have been found to draw up corresponding renewable energy development plans to increase the proportion of renewable energy use. In addition to that, there has been growing development of green energy technologies innovation to stimulate the utilization of renewable energy. In light of this environmental crisis as well, a number of literatures has been conducted to examine the impact of green technology innovations and production efficiency on the energy consumption.

[8] examined the effect of renewable energy technology innovation on carbon intensity in 30 Chinese provinces. Their findings indicated that every 1% increase in the innovation level of renewable energy technology would reduce the carbon intensity by 0.051%. However, this result only holds in the long term. The renewable energy technology innovation does not affect carbon intensity in the short run. Their finding was in consistent with [18] and [29] that demonstrated similar significant impact of green energy technology in reducing carbon emissions. By employing the bootstrapping ARDL-bound testing technique, [27] similarly revealed that green technology innovation and renewable energy use reduce the carbon dioxide emissions.

However, some past findings have shed light on the contradictory results found on the effect of green technology innovations on environment degradation. According to [1], the effect of green technology innovations on carbon emissions can be positive or negative under different conditions. As evident in some literatures such as [31], they argued that energy-efficient innovation technologies are found to be less significant to environmental pollution. [14] argued that despite the advancement of technology innovation, most developing countries still rely heavily on conventional energy resources. Hence, the technology innovations would result in an increase of carbon emission instead. This argument was supported by [4] that showed technology innovation tends to increase environmental pollution instead. Similarly, [11] revealed that green technology innovations do not significantly contribute to reducing the carbon dioxide emissions for the economies whose income levels are below the threshold. Hence, it is noteworthy for an investigation in view of the conflicting findings found by past literature.

Meanwhile, some other literatures such as [7, 24, 26] focused on the hypothesis testing on the relationship between economic growth and energy intensity. Findings by [26]) using the cointegration test and Augmented Mean Group estimator showed that economic growth decreases energy intensity for high and upper-middle income country groups. However, this relationship was not found for lower-middle income country group. They suggested therefore, that the negative relationship between economic growth and energy intensity increases as countries reach from low-income level to high. Their findings were in consistent with [5, 10, 19]. By employing the flexible piecewise linear regression, [10] proved that economy growth in low-income countries will lead to rapid improvement to their energy intensities. Similarly, [19] demonstrated robust evidence to support the negative relationship between energy intensity and economic growth by using least squares regression and general method of moment in their analysis.

In another finding by [5], the panel cointegration test result revealed that energy efficiency positively influences the economic growth in the long term. Similarly, [24] showed strong evidence of long-run bidirectional causality between lower energy intensity and higher economic growth for middle-income economies. On the other hand, [3] stressed energy efficiency as one of the significant actors for economic growth. The results of their panel Autoregressive Distributed Lag (ARDL) supported the hypothesis that economic growth positively impacts carbon emissions. [7] contributed to the debate by analyzing the relationship between energy efficiency and economic performance at the micro- (total factor productivity) and macro-level (countries' economic growth). They presented the empirical evidence that lower levels of energy intensity are associated with higher total factor productivity for majority of the developing countries studied. In other words, the higher energy efficiency is associated with higher total factor productivity in the manufacturing sector. Hence, signified the negative relationship between energy intensity and GDP per capita.

In conclusion, some studies presented positive findings on the relationship between energy technology innovation and energy intensity, while others provided empirical evidence of negative results instead. The same case applies for the relationship between economic growth and energy intensity. These divergent findings offer gap for some comprehensive studies to be conducted within the context of Malaysia. Besides that, the studies on the effects of green technology innovations and production efficiency on energy intensity in Malaysia has remained relatively few. Furthermore, most studies have been focusing on the relationship between economic growth and energy intensity. But very little research has been done to empirically investigate implications of the green technology innovations and production efficiency in environment. This study will attempt to fill the literature gap and has novelty value with the examination of the effects of the combination both green technology innovations and production efficiency in environment.

## 3 Methodology

### 3.1 Model Construction

Based on Mahmood et al., (2020) model, the following energy-output nexus adopted to find proper relationship between energy intensity and economic growth:

$$InE_t = \alpha + \gamma InY_t + \varepsilon_{it} \quad (1)$$

*where* $0 < \gamma < 1$

In Eq. (1), $E_t$ is total primary energy consumption at time t and $Y_t$ denoted the gross domestic product at time t. Both variables are in natural log. By adding on both side $-$ $InY_t$, it gives the intensity form:

$$InE_t - InY_t = \alpha + \gamma InY_t - InY_t + \varepsilon_t \tag{2}$$

$$In\left(\frac{E_t}{Y_t}\right) = \alpha + \beta InY_t + \varepsilon_{it} \tag{3}$$

Where $\beta = (\gamma - 1)$

To assess the extent to which green technology innovations and production efficiency in environment can affect energy intensity, this study included

$$In\left(\frac{E_t}{Y_t}\right) = \alpha + \beta_1 InY_t + \beta_2 InGTI_t + \beta_3 InSNMI_t + \beta_1 InR\&D_t + \varepsilon_t \tag{4}$$

Equation (4) indicates a green technology innovation (GTI) which proxy by patents in environment-related technologies, the Sustainable Nitrogen Management Index (SNMI) proxy for environmental performance of the agricultural production, and Government allocation for research and development (R&D).

Although much study has been done on economic growth and energy intensity, less has been done on the implications of the green technology innovations and production efficiency in environment. Following [26] hypothesis, "economics growth decreases energy intensity" hence expected to have negative relationship. Despite the fact that it is extremely limited empirical study examine the association between green technology and energy intensity, our study predict that green technology innovations may motivated more energy efficiency and thus reduce energy intensity. According to [32] productions can become more energy efficient and green through cultivating sustainable and green practices. Hence, similar prediction on the effect of production efficiency in environment toward the energy intensity. The government expenditure on R&D include as control variable and expected to have negative impact on energy intensity.

### 3.2 Data Description

This study used the annual data in 15 Emerging and Growth-Leading Economies (EAGLEs)[1] from 2000 until 2018. The country selection was based on its current

**Table 1.** Countries used in the study

| Countries |
|---|
| Malaysia, Vietnam, Algeria, Colombia, Turkey, Philippines Mexico, China, Pakistan, Indonesia, India, Brazil, Egypt, Iran, Nigeria |

[1] EAGLEs is a grouping acronym coined by BBVA Research in 2010 to designate all emerging economies likely to contribute more to global economic growth in the next ten years than the G6 economies on average (G7 excluding the U.S.).

**Table 2.** Description and Unit of the Data

| **Variable** | **Data Description** | **Unit of Measurement** | **Source** |
|---|---|---|---|
| Energy Intensity ( $\frac{E_t}{Y_t}$ ) | the amount of energy used to produce a given level of output or activity | Total Energy intensity (MJ/constant 2010 US$ GDP) | World Development Indicators |
| Economic Growth (Y) | The sum of gross value added by all resident producers in the economy, plus any product taxes and minus any subsidies not included in the value of the products. | Gross domestic product (constant 2010 US$ | World Development Indicators |
| Green Technology Innovations (GTI) | Patents in environment-related technologies | output of environmental innovation | OECD statistics database |
| The Sustainable Nitrogen Management Index (SNMI) | Environmental performance of the agricultural production. Here, the SNMI is defined based on two important efficiency terms in crop production, namely Nitrogen Use Efficiency (NUE) and land use efficiency (crop yield). | Sustainable Nitrogen Management Index (best 0–1.41 worst) | Zhang and Davidson (2019) |
| Government allocation for research and development (R&D) | Gross domestic expenditure on scientific research and experimental development (R&D) expressed as a percentage of Gross Domestic Product (GDP). | Expenditure on research and development (% of GDP) | OECD statistics database |

EAGLEs Economic Outlook Annual Report (2016) and the availability of data. Table 1 presents country groups selected for our study. Meanwhile Table 2 presents the variables descriptions.

**Table 3.** Serial correlation, Cross-sectional Dependency Test, Testing of Slope Homogeneity and Unit root test

| | CD test | CIPS | | | |
|---|---|---|---|---|---|
| | | CIPS without trend | | CIPS with trend | |
| | | Level | 1st Diff | Level | 1st Diff |
| $\left(\frac{E_t}{Y_t}\right)$ | 13.4* | -1.445 | -3.881*** | -2.840* | -3.967*** |
| $Y_t$ | 6.33* | -2.465* | -5.768*** | -2.963* | -5.611*** |
| $GTI_t$ | 5.86* | -2.887* | -7.946*** | 2.087 | -6.991*** |
| $SNMI_t$ | 12.37* | -3.449 | -3.944*** | -3.176* | -4.001** |
| *R&D* | 9.55** | -3.795* | -5.910*** | -3.111 | -5.132*** |
| Modified Wald | 2005* | | | | |
| Wooldridge test | 1209*** | | | | |

Notes: CIPS test developed with the command of xtcips of stata 14 with 3 maximum lags; the critical value for CIPS statistics at (***) 1%, (**) 5%, and (*) 10% level. The null hypothesis is that the variable is homogeneous non-stationary

### 3.3 Testing Slope Homogeneity and the Cross-Sectional Dependency

The presence of a heterogeneous slope is one of the issues with panel statistical analysis. Thus, the estimation starts with testing the serial correlation using the Wooldridge test and the presence of heteroscedasticity using the modified Wald test as reported in Table 3. The results conclude there is a cross-sectional dependence among Emerging and Growth-Leading Economies (EAGLEs. Besides, the error structure is assumed to be heteroskedastic and auto-correlated due to possibly correlation between the groups [13]. The error structure is assumed to be heteroskedastic and auto-correlated due to possibly correlated between the groups. Second, the results from the panel unit root test using the [23] CIPS test revealed that there are mixed results at level. At first different all variables were found to be stationary. These results implied that any possible shock affecting the series is only a temporary effect.

### 3.4 Estimating Dynamic Common Correlated Effects (DCCE)

The Dynamic Common Correlated Effects (DCCE) estimator developed by [9] is used in this paper, which considers heterogeneous coefficients. According to [13], cross-section independence has rarely been seen in macro panels empirical studies, hence, indicated a high possibility of countries specific effects. Therefore, DCCE was chosen because of the potential for countries specific effect among Emerging and Growth-Leading Economies. This estimates the presence of unknown types of error cross-section dependence due to common stock and interdependencies, heterogeneity among the sample, and endogeneity resulting from dynamic panel settings. This estimator provides clearer insight of the presence of unknown types of error cross-section dependence due to common stock and interdependencies, heterogeneity among the sample, and endogeneity from dynamic panel settings. To keep it brief, lets the model simplify as in Eq. (5).

$$y_{it} = \alpha_i + \lambda_i y_{it-1} + \beta_i x_{it} + \sum\nolimits_{t=0}^{pT} \delta'_{it\overline{Z}_{t-1}} + \varepsilon_{it} \tag{5}$$

Where,

$\overline{Z}_t = (\overline{y}_t, \overline{y}_{t-1}, \overline{x}_t)$

$pT$ =The number of lags ($pT = \sqrt[3]{T}$)

$\lambda_i$ = individual heterogeneity factor loading

$\beta_i$ = the heterogeneous coefficient and randomly distribute around common mean

$$\beta_i = \beta + \upsilon_{i,} \upsilon_i \sim IID(0, \Omega_V)$$

From Eq. 3, $\lambda_i$ and $\beta_i$ are stacked into $\pi_i = (\lambda_{it,} \beta_i)$. The mean group coefficient estimates as in Eq. (6):

$$\widehat{\pi}_{MG} = \frac{1}{N} \sum\nolimits_{i=1}^{N} \widehat{\pi}_i \tag{6}$$

Where $\widehat{\pi}_i$ and $\widehat{\pi}_{MG}$ are consistently estimated with convergence rate $\sqrt{N}$ if $(N, T, pT) \Rightarrow \infty$

The asymptotic variances can be consistently under the full rank of factor loading estimation by:

$$Var(T_{MG}) = N^{-1} \sum\nolimits_{\pi}^{\Lambda} = \frac{1}{N(N-1)} \sum\nolimits_{i=1}^{N} \left(\hat{\pi}_i - \hat{\pi}_{MG}\right)(\hat{\pi}_i - \hat{\pi}_{MG})' \tag{7}$$

The mean group estimates have the following asymptotic distribution:

$$\sqrt{N}\left(\hat{\pi}\_MG - \pi\right) \rightarrow N(0, \sum\nolimits_{MG}) \tag{8}$$

Furthermore, within the dynamic environment, the dynamic common correlated effect allows for Pooled Mean Group (PMG) estimations. According to [23], the PMG estimators are the intermediary between heterogeneous and homogeneous coefficients. By adding cross-sectional means and lags, this estimator will be able to control the dependency. Furthermore, utilising the jackknife correction method and the recursive mean adjustment provided by [9], this estimator can calibrate a small sample times series bias. The mean group estimate of the Jackknife bias corrected DCCE estimators as follows:

$$\widehat{\pi}_{MG} = 2\widehat{\pi}_{MG} - \frac{1}{2}(\widehat{\pi}_{MG(a)} + \widehat{\pi}_{MG(b)} \tag{9}$$

*Where,*

$\hat{\pi}_{MG(a)}$ – Mean group estimate of the first half ($t = \frac{T}{2} + 1, \ldots, T$)

$\widehat{\pi}_{MG(b)}$ – Mean group estimate of the second half ($t = 1 \ldots \frac{T}{2}$)

The Jackknife derived by first, estimating the first half of the existing period ($\hat{\pi}_{MG(a)}$) and the second half ($\hat{\pi}_{MG(b)}$) separately then taking the average value of the Mean Group

Dynamic Common Correlated Effect. Interestingly, the estimation also generates cross-sectional dependence (CD) test. The employment of the Dynamic Common Correlated Effects (DCCE) model due to several reasons.

Hence, this study use model from Eq. (4) in panel setting and consider the dynamic heterogeneity specification as follow:

$$In\left(\frac{E}{Y}\right)_{it} = \alpha + \beta_1 InY_{it} + \beta_2 InGTI_{it} + \beta_3 InSNMI_{it} + \beta_1 InR\&D_{it} + \lambda_i f_t + \varepsilon_{it} \quad (10)$$

Where the $i = 1 \ldots$ N, and t = 1 … T denotes to the cross-section and times of the panel respectively. To estimate the dynamic effects and heterogeneity across countries, the lagged value of green technology innovation is included in the equation. Meanwhile, the error term capturing the unobserved country-specific effect ($f_t$) that includes the individual heterogeneity factor loadings ($\lambda_i$) and the remaining disturbance term ($\varepsilon_{it}$).

## 4 Results

Table 4 reports estimation results using the Dynamic Common Correlated Effects (DCCE) estimators in 15 emerging and growth-leading economies countries from 2000 until 2018. The Mean Group Dynamic Common Correlated Effect (MG-DCCE) is the core explanatory estimation, nonetheless the estimations also taking account the estimations using Jackknife bias correction and Recursive mean adjustment method. The Jackknife and recursive methods are used to verify the robustness of the studies since they allow for small sample time series bias corrections. The estimated coefficient the lagged energy intensity found to be a statistically significant positive influence on the current energy intensity at a 5% significance level. This justifies that the use of the dynamic panel data model and implied that an increase in energy intensify in the previous year intensifies more energy in the following year.

The green technology innovations exert a negative effect on energy intensity based on mean group DCCE. It is demonstrated that a 1% increase in green technology innovations will cause a reduction in energy intensity by 0.8821% in mean group DCCE. The negative effects were also agreed by few studies such as [8] and [30].

Whilst an improvement in environmental performance of the agricultural production in term of nitrogen use efficiency (NUE) and land use efficiency will reduce the energy intensify. Statistically shows that the coefficient of the Sustainable Nitrogen Management Index (SNMI) demonstrated that with every 1% increase in environmental performance of the agricultural production, the energy intensity decreases by 1.482%. In terms of expenditure on research and development, the empirical analysis reveals that the government allocation for research and development (R&D) has a negative impact on energy intensity although shows a statistically insignificant relationship.

Interestingly, energy efficiency has not improved as a result of economic expansion in emerging and growth-leading economies. Based on the result estimation, indicates that every 1% in economic growth in emerging countries necessitates an increase of 0.6247 in energy intensity. This result supported the argument by [24] and [34] developed countries' energy intensity is decreasing as their economies grow, whereas developing countries' is growing.

**Table 4.** Result Estimation for Dynamic Model using the DCCE Estimators

| **Variable** | **Mean Group (MG)** | **Jack-knife Bias Correction** | **Recursive mean adjustment method** |
|---|---|---|---|
| $\left(\frac{E_t}{Y_t}\right)$ | 0.3202***<br>(0.074) | 0.2737***<br>(0.4516) | 0.0778***<br>(0.1960) |
| $Y_t$ | 0.6247**<br>(0.0626) | 1.4169**<br>(2.883) | 0.1623**<br>(0.1445) |
| $GTI_t$ | -0.8821**<br>(0.234) | -0.3341**<br>(0 .0521) | -0.034**<br>(0.0214) |
| $SNMI_t$ | -1.482<br>(1.023) | -1.377*<br>(1.220) | -1.244<br>(1.192) |
| *R&D* | -0.475<br>(0.027) | -0.855<br>(0.109) | 0.850<br>(0.145) |
| Constant | 1.084**<br>(0.846) | 1.281<br>(0.700) | 1.056**<br>(0.725) |
| *Obs.* | 240 | 240 | 220 |
| *R-squared* | 0.84 | 0.79 | 0.84 |
| *CD Statistic (p-value)* | -1.37<br>(0.0713) | -1.42<br>(0.059) | -2.38<br>(0.077) |

Notes: The dependent variable is the energy intensity (lnE/Y). All variables are expressed (*) significant at the 10% level, (**) significant at 5% level, and (***) significant at the 1% level. The analysis uses dynamic common correlated effects estimation developed by Chudik and Pesaran (2015). Figure in parentheses is standard error, Cross Sectional Dependence (CD) test which is p-value, and the null hypothesis is that the error terms are weakly cross-sectional dependent

For robust check, the results of the estimation of Jackknife bias correction and the Recursive mean adjustment method implied that there is no small sample time series bias on the sample. The sign and significant levels of all variables are consistent with the results in Mean Group Dynamic Common Correlated Effect (MG-DCCE), which indicates that the main estimation results are robust.

Next, based on the results, the CD statistics and its P-value that test for the cross dependencies show that the result does not reject the null hypothesis which claimed that the error terms are weakly cross-sectional dependence (p-value > 0.005). The value of goodness-of-fit measures (R-square) for all model indicates the model explains 84% of the cross-country variation for the mean group DCCE, 79 and 84% if consider the Jackknife bias correction and Recursive mean adjustment method, respectively.

## 5 Conclusion

This study examines effects of green technology innovations and production efficiency on energy intensity in the emerging and growth-leading economies. The empirical analysis using the Dynamic Common Correlated Effects (DCCE) shows that energy intensity is significantly reduce in response to more energy-efficient technologies introduce. It is also noted that the emerging and growth-leading economies have been able to be more energy efficient as result of improving the environmental performance of the agricultural production and spent more on R&D. Nonetheless, it is proven that balanced against the rapid increase in economic growth and improving energy efficiency in emerging and growth-leading economies is the most difficult task.

The findings of the current study could have a number of policy implications. Firstly, designing efficient energy policy necessitates a thorough understanding of the relationship between green technology innovations with energy intensity. This results also justify the importance of financial and technical support to boost technological progress, as well as investment for scientific research and innovation which will benefit country energy industries. Secondly, the policies must be designed such that new technology and energy efficient effort could create and promotes a new income stream and providing positive spillover effect to the local economy. Thirdly, partnership among the emerging and growth-leading economies is crucial for achieving the SDGs. It is critical that all countries are able and willing to mobilise the necessary financial resources share knowledge and innovative technologies; and disseminate knowledge and share innovative technologies.

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