Carbon Emission Driving Mechanisms and Decoupling Effects in Liaoning Province from the Perspective of Industrial Heterogeneity: An Empirical Analysis Based on LMDI and Tapio Models

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Abstract. Against the backdrop of the dual carbon strategy, low-carbon transition in Liaoning Province is highly urgent. From the perspective of industrial heterogeneity, this study divides Liaoning's industries into high energy-intensive and high-emission sectors and low energy-intensive and low-carbon sectors. Using the LMDI additive decomposition method and Tapio decoupling index model, it identifies carbon emission drivers and analyzes decoupling characteristics between economic growth and carbon emissions. The results show that carbon emissions in Liaoning are dominated by high energy-intensive sectors, where economic output is the main driving force for emission growth and energy intensity is the key to emission reduction. Low energy-intensive sectors maintain steady emission reductions supported by both energy intensity and carbon intensity effects, with little impact from economic output. Liaoning's overall decoupling fluctuates significantly with obvious industrial heterogeneity. High energy-intensive sectors are mainly in unstable weak decoupling and rely heavily on energy intensity, while low energy-intensive sectors basically achieve strong decoupling. Divergent driving forces lead to different decoupling performances: a single emission reduction path limits decoupling quality in high energy-intensive sectors, whereas diversified mitigation measures weaken the economic-emission linkage in low energy-intensive sectors. Accordingly, this paper proposes classified industrial regulation, further energy efficiency improvement and energy structure optimization in high energy-intensive industries, and consolidation of emission reduction achievements in low energy-intensive industries, so as to support deep decoupling of economic growth from carbon emissions for Liaoning and similar old industrial bases.

Keywords: Industrial Heterogeneity, LMDI Decomposition, Carbon Emissions, Decoupling Effect, Liaoning Province.

1 Introduction

Against the backdrop of deepening global climate governance and the implementation of China's "Dual Carbon" strategy [1], decoupling economic development from carbon

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emissions is critical to high-quality regional development. As a major heavy industrial base, Liaoning Province has long featured a high-carbon industrial structure and coal-dominated energy consumption, with large total carbon emissions mainly contributed by energy-intensive sectors. Effective carbon reduction during its revitalization is therefore practically urgent and empirically instructive.

Existing research has primarily focused on two strands: the driving factors of carbon emissions and the decoupling between economic growth and emissions. The Logarithmic Mean Divisia Index (LMDI) is widely adopted due to its residual-free, highly interpretable decomposition. Ma (2018); Chen (2023) show that economic output dominates emission growth in Liaoning and the three northeastern provinces [2], whereas falling energy intensity serves as the key abatement channel [3]. The Tapio model further identifies considerable industrial and regional heterogeneity [4], driven by divergent forces. Research on carbon emission drivers from an industrial heterogeneity perspective has deepened [5], with the LMDI-Tapio framework widely applied to decoupling assessment in manufacturing and old industrial bases [6]. Nevertheless, current literature remains limited in three respects. First, insufficient attention is paid to industrial heterogeneity, as most analyses remain at the provincial aggregate level without refined sectoral examination tailored to Liaoning's heavy industry-oriented structure. Second, research lacks specificity for old industrial bases and insufficiently reflects Liaoning's strong carbon lock-in and rigid industrial transition, thus restricting its value for targeted emission reduction policies.

Based on this, this paper focuses on Liaoning Province from an industrial heterogeneity perspective, combining the LMDI additive decomposition method and the Tapio decoupling index model to construct an integrated framework of "industrial classification-driver identification-decoupling analysis-mechanism revelation". It addresses two core issues: identifying the key drivers of carbon emissions in heterogeneous industries and quantifying their divergent mechanisms; analyzing decoupling patterns at the provincial and sectoral levels, and revealing how drivers influence decoupling states. This paper contributes in three aspects: first, a refined perspective that classifies heterogeneous industries by energy intensity and carbon intensity, well matching Liaoning's industrial structure; second, a systematic framework that links driving mechanisms with decoupling relationships; third, targeted practical implications that explain the weak decoupling stability of energy-intensive industries and provide differentiated emission reduction pathways for Liaoning and similar old industrial bases.

2 Research Design

To achieve a joint analysis of carbon emission drivers and decoupling effects, this study adopts a combined framework of the LMDI additive decomposition method and the Tapio decoupling index model. The LMDI method is used to decompose the driving forces of carbon emission changes in the two heterogeneous industry groups, quantify the contribution of each factor, and identify the core drivers. The Tapio model characterizes the decoupling state between economic growth and carbon emissions and reveals the decoupling differences between the two industry types. Together, they form a progressive logic of "drivers-outcomes". By explaining decoupling differences through divergent driving factors, this paper ultimately reveals the internal linkage between carbon emission mechanisms and decoupling effects in Liaoning Province from an industrial heterogeneity perspective, providing a scientific basis for formulating targeted emission reduction policies.

2.1 Classification of Industrial Heterogeneity

To identify the sectoral sources and heterogeneous characteristics of carbon emission changes in Liaoning Province, this study aggregates the provincial economy into six core sectors in accordance with the Industrial Classification for National Economic Activities (GB/T 4754-2017) and the region's heavy industry-dominated structure: agriculture, forestry, animal husbandry and fishery; industry; construction; transportation, warehousing and postal services; wholesale, retail, accommodation and catering; and other services.

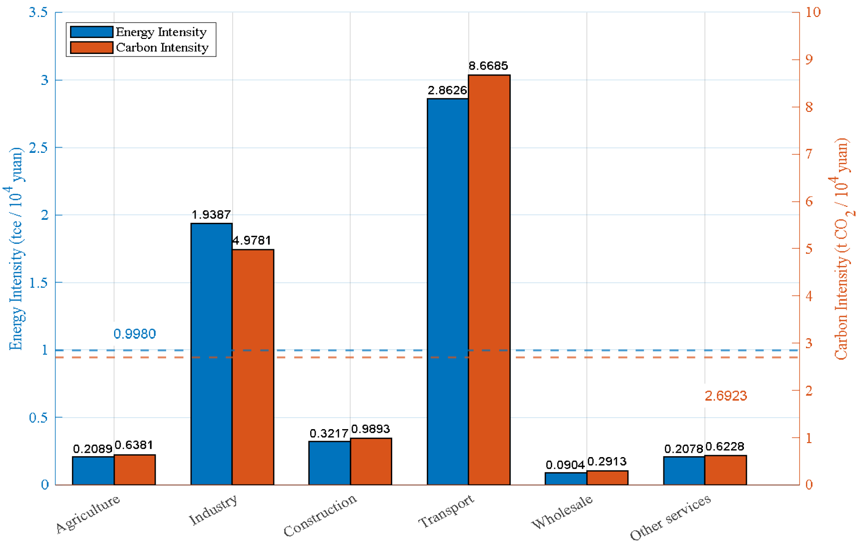

Fig. 1. Calculated energy intensity and carbon intensity for six major industrial sectors in Liaoning Province

Based on provincial and national statistical yearbooks (2016-2024), carbon emissions from energy activities in production sectors are calculated using the method by Cong Jianhui et al. (2014) [7], combined with IPCC (2006) default emission factors and annual power emission coefficients for Liaoning Province. Two classification indicators are constructed: energy intensity ($EI_i = \frac{E_i}{G_i}$) and carbon intensity ($CI_i = \frac{C_i}{G_i}$), reflecting low-carbon performance from energy conservation and carbon reduction perspectives. Here EI_i and CI_i represent energy intensity and carbon emission intensity respectively; E_i is the total energy consumption of the i-th industry (10,000 tons of standard coal), G_i is the value added of the i-th industry (100 million yuan), and C_i is the carbon emissions of the i-th industry (10,000 tons of CO_2). The combination of the two dimensions results in four scenarios: high energy consumption-high carbon emission, low energy consumption-low carbon, high energy consumption with a clean energy structure, and low energy consumption dependent on high-carbon energy. This analysis identifies whether the core contradiction of industrial carbon emissions lies in insufficient energy efficiency or a high-carbon energy structure, providing a theoretical basis for differentiated emission reduction pathways.

Using 2015-2022 as the study period, average values of the two indicators for six major sectors are calculated, as presented in Figure 1. A 20% threshold relative to the provincial average is adopted to robustly classify sectors into two groups: high energy consumption and high emission industries (industry; transportation, warehousing and postal services) and low energy consumption and low emission industries (the remaining four).

2.2 Driving Factor Identification

Decomposition Dimensions and Variable Definitions. This study employs the LMDI additive decomposition to analyze carbon emission drivers. This approach offers residual-free decomposition, unique solutions, and strong interpretability, with its additive form enabling direct quantification of factor contributions. Carbon emission changes are decomposed into four core effects: carbon intensity, energy structure, energy intensity, and economic output. Factors with limited influence, such as population, are excluded to better reflect the reality of industrial carbon emissions in Liaoning Province. An industrial-level LMDI model is established, with definitions and units of core variables presented in Table 1.

Table 1. Definitions of core variables in the LMDI decomposition model

Variable	Meaning	Unit
C	Total carbon emissions of the industry	10,000 tons of CO_2
C_{ij}	Carbon emissions from the j-th energy source in the i-th industry	10,000 tons of CO_2
E_{ij}	Consumption of the j-th energy source in the i-th industry	10,000 tons of standard coal
E_i	Total energy consumption of the i-th industry	10,000 tons of standard coal
G_i	Added value of the i-th industry	100 million yuan
CI_{ij}	Carbon intensity of the j-th energy source in the i-th industry (C_{ij}/E_{ij})	tons of CO_2/ton of standard coal
ES_{ij}	energy source in the total energy consumption of the i-th industry (E_i/E_{ij})	%
EI_i	Energy consumption per unit added value of the i-th industry (E_i/G_i)	tons of standard coal/10,000 yuan

Decomposition Model Construction. Decomposition Model Construction. Based on the accounting identity of total carbon emissions, the total carbon emissions of sector i are decomposed into the product of four factors: carbon intensity, energy structure, energy intensity, and economic output. The basic LMDI decomposition model is specified as follows:

$$C = \sum_{i=1}^{2}\sum_{j=1}^{4}\frac{C_{ij}}{E_{ij}}\times\frac{E_{ij}}{E_i}\times\frac{E_i}{G_i}\times G_i \tag{1}$$

$$= \sum_{i=1}^{2}\sum_{j=1}^{4} CI_{ij}\times ES_{ij}\times EI_i\times GI \tag{2}$$

In the formula, i=1, 2 denote high energy-intensive and high-emission industries and low energy-intensive and low-emission industries, respectively; j=1, 2, 3, 4 denote four energy types: coal, oil, natural gas, electricity. The total change in carbon emissions over the study period is decomposed into the sum of contributions from each driving factor. Let the total carbon emissions in the base period (2015) be C^0, and the total carbon emissions in the target period (year T, where T ranges from 2016 to 2022) be C^T. Then the total change in carbon emissions $\Delta C = C^T - C^0$, and the total change can be decomposed into four parts: carbon intensity effect (△ CI), energy structure effect (△ ES), energy intensity effect (△ EI), and economic output effect (△ G), namely:

$$\triangle C = C^T - C^0 = \triangle CI + \triangle ES + \triangle EI + \triangle G \tag{3}$$

In the formula, △ CI, △ ES, △ EIand △ Gdenote the changes in carbon emissions driven by the carbon intensity, energy structure, energy intensity and economic output effects, respectively. A positive value indicates that the factor contributes to emission growth, while a negative value implies an emission-inhibiting effect.

The quantitative expression for the carbon intensity effect is given in Equation (4). Other effects adopt similar formulations and are thus omitted.

$$C = \sum_{i=1}^{2}\sum_{j=1}^{4}\frac{C_{ij}^T - C_{ij}^0}{\ln C_{ij}^T - C_{ij}^0}\times\ln\frac{CI_{ij}^T}{CI_{ij}^0} \tag{4}$$

2.3 Decoupling Analysis

Construction of Decoupling Index Model. This study adopts the Tapio decoupling index model to conduct industry-specific decoupling status analysis, and depicts the relationship between carbon emission changes and economic growth changes through elasticity coefficients. This model can avoid the limitation of base period selection in traditional indices and realize refined division of decoupling status. The magnitude and sign of the elasticity coefficient can directly reflect the decoupling degree and type between economic growth and carbon emissions. Combined with the needs of industry-specific analysis, this study sets the decoupling index model as follows:

$$\mathcal{E} = \frac{\triangle C/C}{\triangle G/G} \tag{5}$$

where Ɛ denotes the decoupling elasticity coefficient (dimensionless), C denotes total carbon emissions, △ Cdenotes the change in carbon emissions relative to the base period, G denotes industrial added value, and △ G denotes its change relative to the base period. Using 2015-2022 as the study period, the decoupling elasticity is calculated annually to determine the yearly decoupling status.

Classification Standards of Decoupling Status: Following the classical Tapio decoupling framework [9], decoupling status is classified into three broad categories: decoupling, coupling, and negative decoupling. Detailed criteria and economic implications are presented in Table 2. Among them, strong decoupling represents the ideal low-carbon state, characterized by economic growth accompanied by declining carbon emissions. Negative decoupling indicates an uncoordinated state, in which economic growth coincides with opposing changes in carbon emissions.

Data and Model Robustness Test. The data used for decoupling analysis are consistent with the above analysis in industry scope, study period, and classification, with data sources unchanged. To test the reliability of the Tapio decoupling index, this study conducts a robustness check using the base-period substitution method. Specifically, the original base year 2015 is replaced with 2016, and decoupling elasticities for the whole province and the two industry groups are recalculated for 2017-2022 and compared with baseline results. The estimations are deemed robust if the decoupling statuses from the two sets of calculations are highly consistent.

Table 2. Classification Criteria and Economic Implications of the Tapio Decoupling Index

Core Category	Decoupling Status	Elasticity Coefficient ε Range	$\triangle C$	$\triangle G$	Economic Implication
Decoupling	Strong decoupling	$\varepsilon < 0$	−	+	Economic growth with CO_2 decline (ideal)
	Weak decoupling	$0 < \varepsilon < 1$	+	+	Economic growth with slower CO_2 growth
	Recession decoupling	$\varepsilon > 1$	−	−	Economic contraction with steeper CO_2 decline
Connection	Expansive connection	$\varepsilon = 1$or $0.8 \leq \varepsilon \leq 1.2$	+	+	CO_2 growth roughly aligned with economic growth
	Recession connection	$\varepsilon = 1$or $0.8 \leq \varepsilon \leq 1.2$	−	−	CO_2 decline roughly aligned with economic contraction
Negative Decoupling	Expansive negative decoupling	$\varepsilon > 1$	+	+	Economic growth with faster CO_2 growth
	Weak negative decoupling	$0 < \varepsilon < 1$	−	−	Economic contraction with steeper CO_2 decline
	Strong negative decoupling	$\varepsilon < 0$	+	−	Economic contraction with rising CO_2

3 Empirical Results

3.1 Identification of Sectoral Carbon Emission Drivers

Using the LMDI additive decomposition model, this study decomposes the annual changes in carbon emissions for the two industry groups in Liaoning Province from 2015 to 2022 and quantifies the contribution of each driving factor, with results shown in Table 3. On this basis, the cumulative contribution rate of each factor is computed, and the key causes of divergent driving mechanisms are analyzed in combination with the actual industrial development context.

Table 3. Factor Decomposition Results of Energy-Related Carbon Emissions by Sector in Liaoning Province, 2015–2022 (Unit: 10,000 tons of CO_2)

Study period	△ CI		△ ES		△ EI		△ G	
	i=1	i=2	i=1	i=2	i=1	i=2	i=1	i=2
2015-2016	-7.64	-1.58	238.53	-12.81	-1654.68	-288.93	-985.09	262.67
2016-2017	19.04	3.97	-28.58	32.36	-1898.68	-607.84	2568.78	438.51
2017-2018	-17.57	-3.67	-228.24	33.51	-2059.54	-863.75	3628.25	557.60
2018-2019	13.35	2.75	-217.48	35.20	39.78	-735.22	1517.95	426.42
2019-2020	-29.34	-5.99	883.94	-9.33	7610.06	-463.09	-1599.82	205.52
2020-2021	7.60	1.59	-159.31	-13.49	-9322.71	-259.87	8407.00	425.48
2021-2022	8.30	1.82	293.49	-49.74	-2718.20	-276.01	2761.65	279.69

Annual Driving Effects. The carbon emission trends and driving mechanisms of the two industry groups show significant heterogeneity, which constitutes the core cause of fluctuations in total carbon emissions in Liaoning Province.

High energy-intensive and high-emission industries are the main sources of carbon emissions in Liaoning. Their carbon emissions increased in all years except 2015-2016 and 2020-2021. In terms of driving factors, the economic output effect was the core positive driver of emission growth, with positive and large values in all years except 2015-2016 and 2019-2020. This reflects that, as the economic pillar of Liaoning Province, the growth of industrial value added exerted a rigid pull on carbon emissions. The energy intensity effect acted as the core negative inhibitory factor, showing significantly negative values in most years. The energy structure effect alternated between positive and negative with obvious volatility and failed to form a stable negative contribution.

Low energy-intensive and low-emission industries maintained steady emission reductions overall during the study period, with only a slight increase in 2020-2021. The most significant emission reductions occurred in 2017-2018 and 2019-2020 (2.7595 and 2.7279 million tons of CO_2, respectively). Regarding driving factors, the carbon intensity effect and energy intensity effect were dual core emission reduction factors, which underlay the steady emission reduction. The carbon intensity effect mainly stems from fuel substitution (e.g., coal-to-gas conversion and electrification) and industrial structure optimization (e.g., an increased share of high-tech service sectors within low-energy-consumption industries). Although the economic output effect was positive in most years, its magnitude was much lower than that of high energy-intensive and high-emission industries, with very weak pulling effect, indicating an initial low-carbon development pattern. Despite fluctuations, the energy structure effect contributed little to the total change in carbon emissions.

Cumulative Driving Effects. The results of cumulative driving effects from 2015 to 2022 show that: For high energy-intensive and high-emission industries: the cumulative contribution rate of the economic output effect reached 216.94%, making it the absolutely dominant factor driving emission growth; the cumulative contribution rate of the energy intensity effect was -128.24%, acting as the main emission reduction factor; the carbon intensity effect achieved a weak emission reduction effect; the cumulative contribution rate of the energy structure effect was 11.38%, indicating a lag in the clean energy substitution process during the study period. For low energy-intensive and low-emission industries: the cumulative contribution rate of the energy intensity effect reached 334.08%, representing the core emission reduction driver; the mechanism of the carbon intensity effect is closely linked to fuel substitution and the low-carbon transformation within industries. the cumulative contribution rate of the economic output effect was -232.54%, but its pulling effect on carbon emissions was completely offset by other reduction factors; the cumulative contribution of the energy structure effect fluctuated slightly, with negligible impact on the overall change in carbon emissions.

3.2 Decoupling Analysis of Economy and Carbon Emissions

Based on the Tapio decoupling index model, annual decoupling elasticities for Liaoning Province as a whole and for the two industry groups from 2016 to 2022 are calculated. Decoupling status is determined according to the classification criteria in Section 3.3.2, with results presented in Table 4.

Table 4. Sectoral Decoupling Indices and Decoupling Status in Liaoning Province

Year	Liaoning Province (Overall)		High Energy-Consumption and High Emission Industry		Low Energy-Consumption and Low Carbon Industry	
	Decoupling Status	ε	Decoupling Status	ε	Decoupling Status	ε
2016	Strong decoupling	-4.9039	Expansive connection	1.1946	Strong decoupling	-0.1168
2017	Weak decoupling	0.2143	Weak decoupling	0.2941	Strong decoupling	-0.1955
2018	Weak decoupling	0.5655	Weak decoupling	0.6651	Strong decoupling	-0.3459
2019	Strong decoupling	-0.0623	Weak decoupling	0.0632	Strong decoupling	-0.6324
2020	Expansive negative decoupling	18.1965	Strong decoupling	-5.1479	Strong decoupling	-1.7326
2021	Strong decoupling	-0.1257	Strong decoupling	-0.1022	Weak decoupling	0.5052
2022	Weak decoupling	0.1199	Weak decoupling	0.1208	Strong decoupling	-0.0980

Sectoral Decoupling Characteristics. From 2016 to 2022, the overall decoupling status in Liaoning fluctuated among strong decoupling, weak decoupling, and expansive negative decoupling. Strong decoupling in 2016, 2019, and 2021 was driven by the notably negative contribution of the energy intensity effect in high energy-intensive industries and stable strong decoupling in low energy-intensive industries. Specifically, 2016 was supported by energy conservation and emission reduction policies at the outset of the 13th Five-Year Plan period; 2019 was associated with overcapacity reduction in the iron and steel and petrochemical industries; 2021 was driven by clean energy substitution under the dual carbon targets. Weak decoupling in 2017, 2018, and 2022 resulted from the pull of the economic output effect in high energy-intensive industries, with carbon emissions growing more slowly than the economy. Expansive negative decoupling occurred in 2020: amid the economic slowdown under COVID-19 shocks, combined with capacity recovery in energy-intensive industries and a rising share of thermal power, carbon emissions increased sharply.

The two industry groups displayed distinctly different decoupling characteristics. High energy-intensive industries were dominated by weak and strong decoupling with considerable annual volatility; Their carbon emissions are rigidly driven by the economic output effect; emission growth can hardly be fully offset by the energy intensity effect alone, and energy structure optimization has not generated stable emission reduction contributions, making decoupling susceptible to short-term disturbances. By contrast, low energy-consuming industries exhibit highly stable decoupling, as sustained and considerable emission reductions from energy intensity and carbon intensity effects fully offset the mild emission increases caused by economic output, significantly weakening the nexus between economic growth and carbon emissions. The large fluctuation in the overall decoupling state of Liaoning Province is a combined result of the provincial trend being dominated by the volatile decoupling of energy-intensive industries, with the stable emission reduction of low energy-consuming industries only partially offsetting such fluctuations, so stable decoupling has not been achieved at the provincial level.

Robustness Test Results. To verify the reliability of decoupling index results, this study conducts a robustness check via base-period substitution. Results show that the annual decoupling status of low energy-intensive industries is fully consistent with original estimates. For high energy-intensive industries and Liaoning Province overall, the consistency rate reaches 83.33%, with only 2017 showing inconsistency. This discrepancy arises from divergent changes in carbon emissions in 2017 relative to different base periods. Overall, annual decoupling status remains largely unchanged after base-period replacement, confirming the Tapio decoupling index results are robust, insensitive to base-period selection, and suitable for analyzing sectoral decoupling characteristics.

4 Conclusions and Policy Recommendations

Carbon emission changes in Liaoning are dominated by high energy-intensive industries, where economic output drives emission growth, energy intensity contributes the main reduction, and energy structure optimization yields no stable abatement. Low-carbon industries maintain steady emission reductions, supported jointly by energy intensity and carbon intensity effects, with little pull from economic output. Provincial decoupling fluctuates strongly and shows clear sectoral heterogeneity: high energy-intensive industries rely heavily on energy intensity and remain in unstable weak decoupling, while low-carbon industries achieve stable strong decoupling due to sustained reduction effects. Heterogeneity in driving factors constitutes the fundamental cause of divergent decoupling characteristics between the two industry groups: For energy-intensive industries, the single emission reduction pathway relying on energy efficiency cannot offset the rigid emission growth driven by economic expansion, thus constraining the quality of decoupling; For low energy-consuming industries, diversified emission reduction forces have effectively weakened the linkage between economic growth and carbon emissions, enabling stable and strong decoupling. Against this background, targeted low-carbon policies are proposed for Liaoning's industrial structure: First, improve energy efficiency in high energy-intensive industries through continuous retrofits and stricter energy management to stabilize emission reductions and underpin decoupling. Second, optimize the energy structure by expanding green power trading, promoting coal-to-gas and oil-to-electricity transitions in industry and transport, and raising clean energy consumption. Third, consolidate abatement gains in low-carbon sectors by scaling low-carbon operations, supporting low-carbon upgrading, and encouraging cross-sector low-carbon technology spillovers to achieve synergistic emission reduction.

Limited by the availability of provincial-level macro data, the industrial classification in this study is relatively coarse and fails to reflect disparities in energy structure, emission reduction potential, and other aspects among sub-sectors (e.g., heavy manufacturing vs. energy production) within high energy-intensive industries, which may mask more refined driving mechanisms and decoupling paths. Consequently, the policy recommendations remain at the macro-industrial level and lack operable and differentiated abatement pathways for specific sub-sectors.

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Disclosure of Interests

The authors have no competing interests to declare that are relevant to the content of this article.

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