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ARTICLE

Sustainable Competitive Intelligence for Green Mobility Markets: Competitive Landscape Analysis and Strategic Decision Support in China's Passenger-EV Sector

Inteligência Competitiva Sustentável para Mercados de Mobilidade Verde: Análise do Cenário Competitivo e Apoio à Decisão Estratégica no Setor Chinês de Veículos Elétricos de Passageiros

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ABSTRACT | Purpose: This study develops a Sustainable Competitive Intelligence (SCI) analytical framework that converts public market signals from China's passenger electric-vehicle sector into structured competitive-landscape intelligence, strategic decision support, and a repeatable monitoring-and-feedback logic. **Methodology/approach:** The empirical component is a retrospective, single-vintage analysis of the International Energy Agency Global EV Data 2024 release. The archived historical extract contains no observed post-2023 records used in this analysis; the 2025, 2030, and 2035 STEPS/APS records are retained and analyzed separately as conditional scenario outputs. The analysis combines market penetration, technology shares, HHI, normalized Shannon entropy, demand momentum, charging intensity, first-difference Spearman co-movement diagnostics, scenario sensitivity, and robustness checks. **Originality/Relevance:** The study distinguishes public market analytics from organizational CI capability. Sustainable CI is conceptualized as a recurring cycle of planning, sensing, analysis, dissemination, utilization, governance, feedback, organizational learning, and strategic resilience rather than as a synonym for a green market. **Key findings:** Observed passenger-EV sales reached 8.10 million in 2023 and represented 38% of new passenger-car sales. The 2023 technology HHI was approximately 0.555 and normalized entropy approximately 0.580. Public charging points reached 2.70 million. STEPS and APS both imply 85% passenger-EV sales penetration in 2035, while technology composition—especially FCEV—remains scenario-sensitive. **Theoretical/methodological contributions:** The framework links market, competitive-structure, ecosystem-readiness, and scenario-foresight intelligence to decision-making and a longitudinal feedback loop. Empirical claims are bounded to technology-segment competitive-landscape intelligence; first-difference correlations are exploratory and non-causal.

Keywords | Sustainable competitive intelligence. Electric vehicles. Competitive landscape. Strategic resilience. Organizational learning. Scenario foresight. China

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RESUMO |Objetivo: Este estudo desenvolve uma estrutura analítica de Inteligência Competitiva Sustentável (ICS) que transforma sinais públicos de mercado do setor chinês de veículos elétricos de passageiros em inteligência estruturada do cenário competitivo, apoio à decisão estratégica e uma lógica replicável de monitoramento e feedback. **Metodologia/abordagem:** O componente empírico consiste em uma análise retrospectiva, baseada em uma única versão dos dados, da edição 2024 do Global EV Data da International Energy Agency. O extrato histórico arquivado não contém registros observados posteriores a 2023 utilizados nesta análise; os registros STEPS/APS de 2025, 2030 e 2035 são mantidos e analisados separadamente como resultados condicionais de cenários. A análise combina penetração de mercado, participações tecnológicas, HHI, entropia de Shannon normalizada, momentum da demanda, intensidade de recarga, diagnósticos de co-movimento de Spearman em primeiras diferenças, sensibilidade de cenários e verificações de robustez. **Originalidade/Relevância:** O estudo distingue a análise de mercado baseada em dados públicos da capacidade organizacional de Inteligência Competitiva. A Inteligência Competitiva Sustentável é conceituada como um ciclo recorrente de planejamento, sensing, análise, disseminação, utilização, governança, feedback, aprendizagem organizacional e resiliência estratégica, e não como sinônimo de um mercado verde. **Principais resultados:** As vendas observadas de veículos elétricos de passageiros atingiram 8,10 milhões em 2023 e representaram 38% das vendas de novos automóveis de passageiros. O HHI tecnológico de 2023 foi de aproximadamente 0,555 e a entropia normalizada, de aproximadamente 0,580. O número de pontos públicos de recarga chegou a 2,70 milhões. Tanto o cenário STEPS quanto o APS indicam uma penetração de 85% dos veículos elétricos nas vendas de automóveis de passageiros em 2035, enquanto a composição tecnológica especialmente dos FCEVs permanece sensível aos cenários. **Contribuições teóricas/metodológicas:** A estrutura relaciona inteligência de mercado, inteligência da estrutura competitiva, prontidão do ecossistema e inteligência de foresight de cenários à tomada de decisão e a um ciclo longitudinal de feedback. As afirmações empíricas estão delimitadas à inteligência do cenário competitivo no nível dos segmentos tecnológicos; as correlações em primeiras diferenças são exploratórias e não causais.

Palavras-chave | Inteligência competitiva sustentável. Veículos elétricos. Cenário competitivo. Resiliência estratégica. Aprendizagem organizacional. Foresight de cenários. China.

1. INTRODUCTION

Electric mobility is simultaneously a consumption transition, a technology competition, an infrastructure challenge, and a strategic planning problem. China's passenger-EV market is especially useful for examining these dimensions because rapid growth can coexist with substantial changes in the composition of the technologies that generate that growth. Market expansion alone therefore does not answer the strategic questions faced by firms, suppliers, charging providers, investors, or other ecosystem actors. Competitive Intelligence (CI) is relevant when observable signals are organized around decisions, interpreted relative to alternatives, disseminated to users, and revisited as new evidence becomes available (Madureira et al., 2021; Ranjan & Foropon, 2021; Talaoui & Kohtamäki, 2021).

Green-consumption research has generated important evidence on environmental responsibility, perceived green value, norms, marketing, purchase intentions, and the continuation of sustainable-consumption behavior in China (Yue et al., 2020; Sun et al., 2022; Ji et al., 2024; Li et al., 2024; Zhao et al., 2024; Tong et al., 2025).

Such studies explain why consumers may intend to adopt or continue using environmentally preferable products, but they do not by themselves provide a competitive map of how an aggregate market is changing. Market series, however, are not about motives but rather about actual sales, market shares, stocks, infrastructure and energy transition results. The two kinds of evidence should not be employed as substitutes for each other, but should be used in conjunction with one another.

The issue is not that there are no market data; instead, the challenge is to process the data available and make it usable for decision making. CI scholarship is not solely about ownership of data and dashboards, but rather about the organized sensing, interpretation, dissemination and utilization of these data and dashboards (Lutz & Bodendorf, 2020; Madureira et al., 2023; Qian et al., 2024). In addition, empirical research indicates that organizational routines, maturity and adaptability to change all have an impact on the value of CI (Bao, 2020; Sadeghiani et al., 2022; Tsuchimoto & Kajikawa, 2022; Olszak et al., 2023). This process perspective is particularly relevant for technological transition involving rapid change in historical momentum, technology mix, enabling infrastructure and policy-determined future pathways.

A study of a sustainable market is not, however, necessarily Sustainable Competitive Intelligence for the Journal of Sustainable Competitive Intelligence. The sustainability dimension shall be based on contribution to long-term learning, adaptation, resilience, governance and sustainable competitive value due to the intelligence. Prior work connects analytics and dynamic capabilities to adaptive performance (Mikalef et al., 2020; Mikalef & Gupta, 2021; Yoshikuni et al., 2023), while CI research links organizational learning and resilience to organizational sustainability (Olaleye et al., 2023; Wu et al., 2023). The present study therefore positions public EV-market indicators as external intelligence inputs within a broader SCI cycle rather than treating the indicators themselves as a measured organizational capability.

The empirical unit is also deliberately bounded. The available IEA data describe China-year and China-year-technology observations. They do not contain manufacturer, brand, model, price, patent, product-launch, or firm-strategy fields. The study consequently develops technology-segment competitive-landscape intelligence, not firm-level competitor intelligence. This boundary is analytically important because open-source CI can be valuable only when the claims made from public signals match the granularity of those signals (Lutz & Bodendorf, 2020).

The study addresses four research questions within a deliberately retrospective empirical window. RQ1: What was the change of observed passenger EV demands and market penetration in China over this time period? RQ2: What has changed in the internal BEV, PHEV and FCEV technology structure during the time frame for which the relevant indicators can be correlated? RQ3: Has the development of charging infrastructure and selected transition outcomes tracked each other during the development of EV markets? RQ4: What are the conclusions that hold true in both the IEA STEPS and the APS scenarios in 2035 and what are the conclusions that are specific to the scenarios? The study has three contributions. First, it takes into account market expansion in addition to other measures of concentration and diversification, but does not confuse these with internal technology competition. Second, it removes historical observations from the conditional scenarios, thus eliminating the possibility of mixing the projections of the values at 2025, 2030 and 2035 with the observed values. Third, it embeds these market signals in a Sustainable Competitive Intelligence (SCI) framework which defines the planning, sensing, analysing, disseminating, utilising, governing, feedbacking, learning and resiliency cycle for sustainable strategic decision making. What you will end up with is a monitoring and decision support framework, not a causal attribution and deterministic forecasting framework.

2. THEORETICAL FRAMEWORK

2.1 Competitive intelligence as a decision capability

Competitive Intelligence is not merely a set of metrics; it is an action-oriented organizational process designed to support decision-making. A signal becomes useful intelligence when it is linked to an intelligence need and relevant alternatives, interpreted in a context of uncertainty, presented to an appropriate user, and connected to an action. This process view is aligned with current definitions of CI and maturity models (Madureira et al., 2021, 2023; Maungwa & Laughton, 2023). It also explains why the same data can support different strategic questions depending on an organization's assets, risks, and information requirements.

While digital analytics may enhance sensing and interpretation, analytical capability is not synonymous with any software tool or algorithm. Research on big-data analytics and artificial-intelligence capability highlights complementary organizational resources, routines, and dynamic capabilities (Mikalef et al., 2020; Mikalef & Gupta, 2021; Ranjan & Foropon, 2021; Yoshikuni et al., 2023). Transparent, simple metrics are more appropriate than complex predictive modeling in the present study, especially because the main historical series is short and annual. Methodological restraint therefore becomes an integral part of the intelligence design: reproducibility and traceability are more important than over-optimized predictive performance that cannot be reproduced reliably.

2.2 Sustainable Competitive Intelligence, organizational learning, and strategic resilience

Sustainable Competitive Intelligence is an extension of CI over time to become organizational capability renewal. The proposed logic is that: the environmental and market signals drive CI planning and sensing, which drive analysis and interpretation, dissemination and utilization, feedback and governance, organizational learning, strategic resilience, sustainable strategic decision-making and sustainable competitive advantage. This paper does not attempt to empirically estimate a causal model of this chain; rather, the chain offers a theoretical structure to show how repeated intelligence in the market can enable organizational adaptation in the longer term.

This ability is crucial since the usefulness of a CI process would be negligible if there were no means to revise preconceived notions in the face of credible evidence. However, added value in evidence-use research in CI is not just in the collection of evidence but also the use and adaptation of evidence (Olszak et al., 2023). Previous studies on digital startups offer insights into how intelligence can facilitate pivoting under uncertainty (Sadeghiani et al., 2022), and studies on dynamic capabilities emphasize three aspects: sensing, seizing, and reconfiguring resources (Wu et al., 2023). From the theoretical perspective, the longitudinal feedback component of the current framework is justified by the relationship between competitive intelligence, organisational learning, resilience and organisational sustainability found by Olaleye et al (2023).

In the context of the EV transition, strategic resilience is especially important because it can be necessary to consider several technology corridors, reallocate resources to those technology corridors, or rethink assumptions about infrastructure. No mechanical link between a single public indicator (and superior firm performance) and sustainable competitive advantage exists. Advantage, however, can come when the organization can continuously redefine its intelligence agenda, interpret structural changes, keep its institutional knowledge and change faster and more systematically than other organizations. The strategic significance of environmental innovation, sustainable manufacturing and circular-economy competences have been emphasized in sustainability research (Boiral et al., 2022; Hermundsdottir & Aspelund, 2022; Yu et al., 2022).

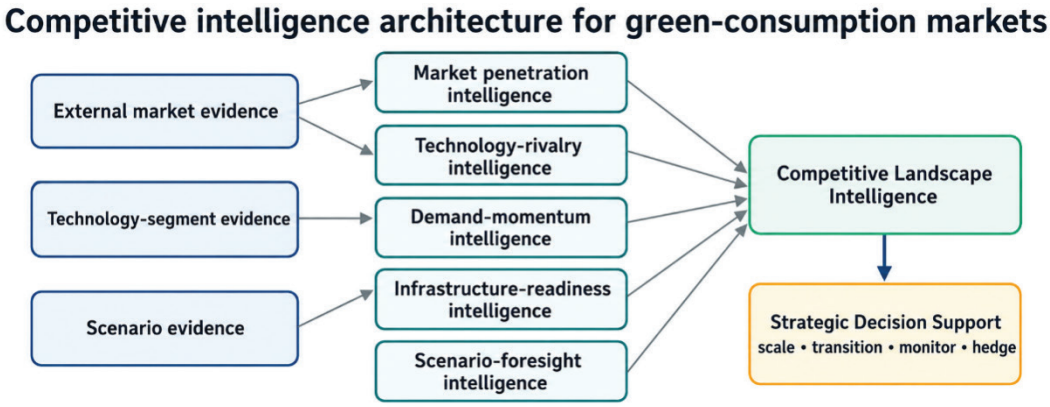

Figure 1. Sustainable Competitive Intelligence architecture for green-mobility markets.

Note. The empirical market series provide external technology-segment signals; the organizational capability pathway is a theoretical interpretation for repeated CI use. The model is informed by Madureira et al. (2021, 2023), Olaleye et al. (2023), Olszak et al. (2023), and Wu et al. (2023).

2.3 Market, competitive-structure, ecosystem, and scenario intelligence

The analytical framework comprises four signal layers. Market intelligence includes absolute demand, market penetration, and installed stock. Competitive-structure intelligence examines whether growth is concentrated in one powertrain or distributed across BEV, PHEV, and FCEV. Ecosystem intelligence examines whether charging and transition outcomes grow in tandem with the installed vehicle stock. Scenario intelligence compares the conditional STEPS and APS pathways to distinguish conclusions that are stable across policy and technology assumptions from those that are sensitive to them.

These layers address different types of strategic uncertainty. Even in a large market, redistribution within the technology mix may be strategically significant. Absolute infrastructure growth can be high while infrastructure intensity grows more slowly as the vehicle stock expands. Two scenarios may agree on EV market share while differing in technology composition. The framework therefore avoids a single composite score and preserves the distinct decision meaning of each signal.

Stakeholder research on the EV transition aligns with a systems perspective. Coordinated implementation and infrastructure development have been critical to the large-scale diffusion of EVs in China (Li et al., 2020). Given the observed variation in charging behavior by vehicle type, location, and conditions, policy settings can influence the market composition of passenger vehicles (Ou et al., 2021), while national charger counts alone do not capture observed variations in charging behavior. Research on the EV transition is also strategic rather than linear, emphasizing portfolio, ecosystem, and sustainable-value considerations (Gouveia et al., 2024; Wang & Zhang, 2025).

2.4 Complementary interpretation of HHI and normalized entropy

The two aspects of technology concentration and diversity are assessed together. As shares become more centralized, the HHI rises and as shares become more evenly distributed, the HHI falls. Normalized Shannon entropy decreases as the distribution becomes more concentrated and increases as technology shares become more balanced. Ambiguity is eliminated by using both measures as a pair because a structural conclusion is directionally consistent across the two measures.

Table 1. Conceptual interpretation of technology HHI and normalized entropy

Technology-share pattern	HHI	Normalized entropy	Interpretation
One technology dominates	Higher	Lower	Greater concentration / lower diversity
Technology shares become more balanced	Lower	Higher	Lower concentration / greater diversity

Note. With three technology categories, HHI is calculated from squared sales shares and normalized entropy is scaled by ln(3).

3. METHOD

3.1 Data source, historical observation window, and analytical scope

The empirical analysis uses the China subset of the International Energy Agency Global EV Data 2024 release (International Energy Agency, 2024). The source contains multiple transport modes and evidence types; the present study focuses on passenger cars and separates historical observations from Stated Policies Scenario (STEPS) and Announced Pledges Scenario (APS) records. The reported source file contains 12,654 global records and 1,138 records after filtering the region to China across the historical and scenario categories used in the original analytical extract.

The empirical observation window was defined a priori as 2010–2023 for passenger-EV indicators and 2014–2023 for public charging infrastructure because the analysis was conducted on one internally consistent archived extract of the IEA Global EV Data 2024 release. In that archived historical extract, observed records terminate in 2023. Records labelled 2025, 2030, and 2035 belong to the STEPS and APS scenario categories and are therefore analyzed in a separate scenario stream rather than treated as realized observations. Accordingly, neither projected 2025 values nor isolated values obtained from a later data vintage are used to extend the historical series. The analytical cut-off is 31 December 2023. The exact local download date of the archived file was not recorded

at the time of acquisition and therefore cannot be reconstructed reliably; this provenance limitation is reported transparently rather than replaced by an estimated date. A contemporary extension to 2024 or 2025 would require a complete rerun using a single newer documented IEA vintage so that all raw indicators, derived measures, figures, tables, correlations, and robustness checks remain methodologically comparable.

The unit of evidence differs by layer but remains aggregate. Market and infrastructure indicators are China-year observations; competitive-structure measures are derived from China-year-powertrain sales before annual aggregation; scenario comparisons are China-scenario-year observations. No firm, brand, model, price, patent, product-launch, household, or individual consumer records are available. Consequently, the study does not estimate firm-level competitor intelligence, consumer psychology, price elasticities, or causal policy effects.

The empirical results in this manuscript rely exclusively on aggregate secondary IEA data. No human-participant survey data are analyzed. Organizational CI capability is therefore discussed theoretically as the process through which organizations could use the public signals, rather than claimed as an empirically measured latent construct.

3.2 Variable construction and competitive-intelligence measures

Passenger-EV sales, sales share, stock, stock share, public charging points, electricity demand, and oil displacement are treated as raw market signals. Technology shares are calculated by dividing BEV, PHEV, and FCEV passenger-car sales by total passenger-EV sales in the same year. All derived concentration and diversity measures use the same technology-share denominator.

The technology Herfindahl–Hirschman Index is calculated as $HHI_t = \Sigma_j s_{jt}^2$, where s_{jt} is the sales share of technology j in year t. An HHI is greater when the shares are more concentrated, and lower when the shares are more equal, as shares are represented as proportions. The 2023 value can be recomputed directly from the reported shares: $0.66662^2 + 0.33331^2 + 0.00006^2 \approx 0.5555$, consistent with the reported HHI of 0.555. If the very small FCEV share is excluded, the HHI is approximately 0.556, leaving the concentration conclusion substantively unchanged.

Normalized Shannon entropy is computed as $-\Sigma_j s_{jt} \ln(s_{jt}) / \ln(3)$, with zero-share terms treated as zero. The larger the number, the more balanced the technology mix. The normalized entropy for the reported 2023 shares is ~0.580. Therefore, HHI and entropy are considered complementary measures; a decline of HHI coupled with an increase in the normalized entropy means a shift towards a more even technology structure. Momentum of demand is expressed in annual growth and compound annual growth rate (CAGR). The common 2014–2023 window is used when infrastructure alignment is assessed, and the 2018–2023 window is used for a sensitivity check. Charger intensity is reported as public charging points per 1,000 EV stock and, as a robustness check, as public charging points per passenger-EV stock. Scenario sensitivity is defined as (APS – STEPS) / mean(|APS|, |STEPS|) × 100. Scenario records are compared descriptively because they are conditional model outputs rather than random samples.

Table 2. Variable definitions and Competitive Intelligence functions

Variable	Status	Measurement	CI function
Passenger EV sales	Raw	BEV, PHEV and FCEV passenger-car sales; vehicles	Market penetration / demand
EV sales share	Raw	EV share of new passenger-car sales; %	Market penetration
Passenger EV stock	Raw	Installed BEV, PHEV and FCEV passenger-car stock	Market maturity
EV stock share	Raw	EV share of passenger-car stock; %	Market maturity
Public chargers	Raw	Public slow + fast charging points	Infrastructure readiness
Electricity demand	Raw	Passenger-EV electricity demand; GWh	Transition outcome
Oil displacement	Raw	Passenger-EV oil displacement; million lge	Transition outcome
Technology share	Derived	Technology sales / total passenger-EV sales	Technology rivalry
Technology HHI	Derived	Σ squared technology sales shares	Concentration intelligence
Normalized entropy	Derived	$-\Sigma s \ln(s) / \ln(3)$	Technology diversity
CAGR	Derived	Compound growth over selected windows	Demand momentum
Charger intensity	Derived	Public chargers per 1,000 EV stock	Infrastructure readiness
Scenario sensitivity	Derived	APS–STEPS difference relative to scenario mean	Scenario foresight

Note. Raw variables are taken from the China subset of International Energy Agency (2024). Derived measures use only those fields. The market indicators are inputs to the analytical CI framework, not direct measures of organizational CI capability.

3.3 Analytical procedure, small-sample boundary, and robustness

The analytical procedure follows five steps. First, the data are filtered to China, passenger cars, and the required historical or scenario category. Second, observed and scenario evidence are kept in separate analytical streams. Third, raw fields are converted into penetration, market-structure, demand-momentum, infrastructure-readiness, transition, and scenario-sensitivity indicators. Fourth, results are interpreted as signal–meaning–uncertainty–decision–monitoring chains. Fifth, alternative operational definitions are used to test whether central strategic interpretations depend on a single metric choice.

Correlation analysis is deliberately limited to exploratory co-movement diagnostics. Spearman correlations are calculated on first differences or annual growth rates over 2015–2023, yielding only N = 9 annual changes. This sample is too small to provide confirmatory inferences, structural modeling or generalizable causal claims. The coefficients therefore describe whether the indicators tended to move together in the same years. Two-tailed p values are treated only as descriptive diagnostics and are not used for confirmatory hypothesis testing.

The secondary market variables are not reflective items of latent constructs; therefore, no SEM is applied. The annual history is too short to support reliable training and testing of machine-learning prediction models for the main demand series. This methodological limit prevents overfitting and preserves traceability from all derived measures to the original public market inputs.

Robustness checks compare the 2014–2023 and 2018–2023 sales-growth windows; the 2023 HHI with and without the very small FCEV share; alternative charger-intensity denominators; and STEPS versus APS assumptions for 2035 penetration and technology-specific outcomes. Robustness

is defined as stability of the strategic interpretation under a reasonable alternative operational choice, not as the production of statistical significance.

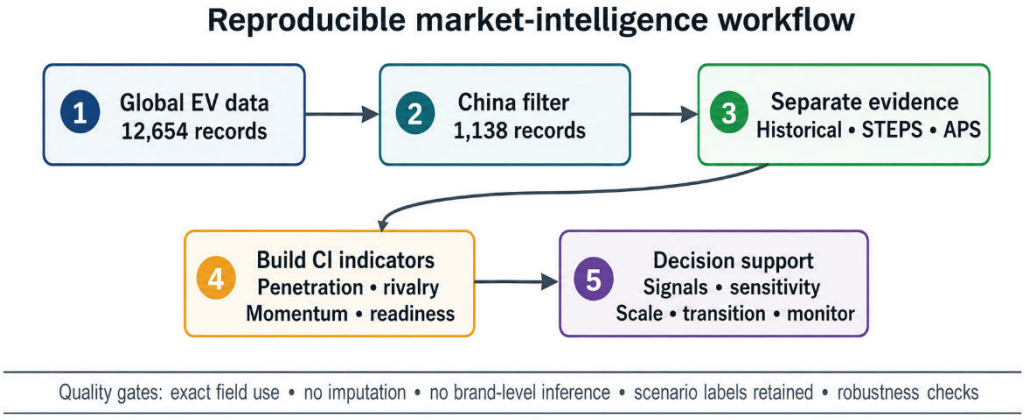

Figure 2. Reproducible fixed-vintage market-intelligence workflow.

Source: authors' design based on International Energy Agency (2024). Historical and scenario records are separated before indicator construction; no firm-level inference is made.

4. RESULTS AND DISCUSSION

Results are organized as Sustainable Competitive Intelligence signals rather than as a sequence of descriptive statistics. Each subsection distinguishes the observed signal, its strategic interpretation, the associated uncertainty, and the monitoring or feedback requirement. This structure moves the discussion from "what happened?" toward "why does the signal matter for a repeatable intelligence cycle?"

4.1 Market-penetration and demand-momentum intelligence

Signal. Passenger-EV sales increased from 1,440 units in 2010 to approximately 8.10 million units in 2023. EV sales share rose from 0.01% to 38%. Total passenger-EV sales increased from 73,000 to 8,100,520 units over the common 2014–2023 period, corresponding to a 68.75% CAGR. The rapid-growth conclusion is not driven solely by the early low base, as the 2018–2023 CAGR remains 49.35%.

Interpretation. The market moved from a very small niche to a substantial share of new passenger-car sales. The key CI implication is that rapid growth, large market scale, and continuing changes in the internal EV market structure occur together. Rapid market growth also increases the risk of relying on static intelligence because capacity assumptions, supplier exposure, and infrastructure assessments can quickly become outdated.

Strategic uncertainty and monitoring. This is a retrospective analysis, and the 2023 endpoint reflects the planned analytical cut-off rather than the state of the market in 2024 or 2025. Strategic implications are therefore framed as retrospective lessons and monitoring rules that can be reapplied

after a full source-vintage refresh. The recommendations are based on the 2023 analytical setting and do not imply that the same conditions continued into 2024 or 2025.

Table 3. Selected descriptive statistics for the common 2014–2023 intelligence window

Variable	N	Mean	SD	Min	Median	Max
Passenger EV sales (vehicles)	10	2,174,378	2,745,242	73,000	1,075,000	8,100,520
EV sales share (%)	10	10.370	13.142	0.400	4.850	38.000
Technology HHI	10	0.635	0.056	0.555	0.635	0.719
Public charging points	10	764,300	877,325	30,000	390,000	2,700,000
Fast-charger share (%)	10	37.700	7.236	20.339	39.874	44.444
Chargers / 1,000 total EV stock	10	136.310	43.538	89.922	124.516	250.836
Electricity demand (GWh)	10	11,126.0	11,928.5	660.0	7,300.0	38,000.0
Oil displacement (million lge)	10	4,353.1	5,939.1	81.0	2,200.0	19,000.0

Note. N denotes annual observations, not independent consumers or firms. Normalized entropy is reported separately for the directly auditable 2023 endpoint under the fixed K = 3 normalization defined in Section 3.2. Source: authors' calculations from International Energy Agency (2024).

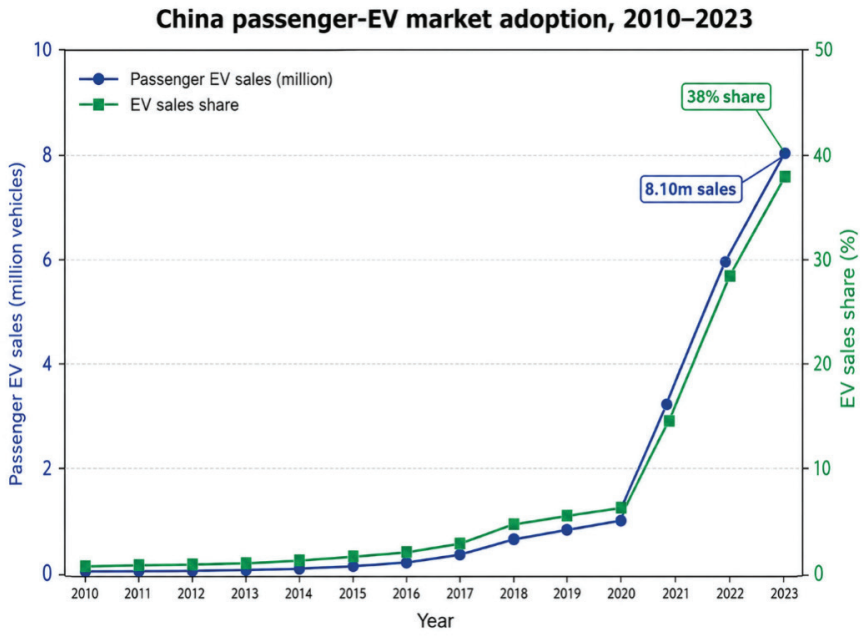

Figure 3. China passenger-EV market adoption, 2010–2023.

Source: authors' calculations from International Energy Agency (2024). The figure shows the observed period in the selected source vintage.

4.2 Technology-rivalry, concentration, and diversity intelligence

Signal. BEV remained the largest passenger-EV technology, but its share of EV sales declined as PHEV expanded. The reported BEV share was approximately 80.7% in 2020, 83.1% in 2021, 74.6% in 2022, and 66.7% in 2023. PHEV correspondingly rose to approximately 33.3% in 2023, while FCEV remained very small in the observed passenger-car data.

Concentration check. The HHI pattern supports the structural conclusion. HHI is higher when one technology has a large market share and lower when shares are more evenly distributed. In 2021, the index stood at approximately 0.719, while in 2023 it declined to approximately 0.555. The 2023 value has been recalculated using the reported BEV, PHEV, and FCEV shares, yielding 0.5555. Normalized entropy follows the complementary trend and is approximately 0.580 in 2023. Thus, the trend through 2023 is toward less concentration and greater diversity, rather than the opposite.

Strategic meaning. Market growth and technology structure convey different intelligence. An organization exposed only to BEV scale could miss the rapid rise of PHEV within a still-growing EV market. Suppliers, infrastructure planners, and investors may therefore need to monitor both total EV demand and relative technology shares. The strategic response is not to rank technologies mechanically but to test whether portfolio, capacity, and ecosystem assumptions remain appropriate as the internal market mix changes.

Feedback requirement. Because the technology mix can change more rapidly than total market penetration, HHI and entropy should be recalculated whenever comparable new technology-level sales data are incorporated. Governance requires preserving the formula, denominator, and treatment of small shares across vintages so that apparent structural change is not an artifact of changing definitions.

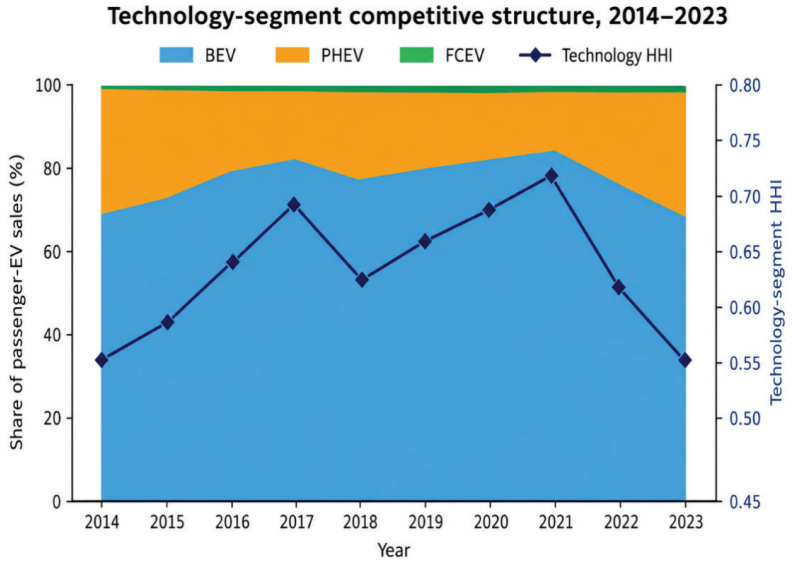

Figure 4. Technology-segment competitive structure, 2014–2023.

Note. HHI is calculated as the sum of squared BEV, PHEV, and FCEV passenger-EV sales shares. Larger HHI indicates greater concentration. Source: authors' calculations from International Energy Agency (2024).

4.3 Infrastructure-readiness and transition intelligence

Signal. Public charging points increased from approximately 30,000 in 2014 to 2.70 million in 2023. The absolute infrastructure signal is therefore strongly positive. However, charger intensity depends on the denominator. For 2023, the reported values are approximately 115.19 public points per 1,000 total road EVs and 123.85 per 1,000 passenger EVs.

Interpretation. Absolute infrastructure expansion does not automatically imply that infrastructure readiness improved at the same rate as vehicle deployment. The stock-adjusted ratio is a macro monitoring signal rather than a direct measure of local access, utilization, reliability, queueing, charging power, or private charging. Empirical charging research demonstrates substantial heterogeneity in charging patterns that national totals cannot represent (Li et al., 2023), while the evolution of China's charging and swapping industry highlights the importance of system-level planning (Wang & Zhang, 2025).

Strategic uncertainty and monitoring. The relevant CI question is whether the denominator-adjusted infrastructure signal deteriorates, stabilizes, or improves as stock grows. Site-level investment decisions require additional geographic and operational data. At the national level, the ratio functions as an early-warning indicator that should trigger more granular analysis rather than as a verdict that infrastructure is sufficient or insufficient.

4.4 First-difference co-movement diagnostics

The first-difference screen reduces, but does not eliminate, the risk of spurious association among strongly trending level series. With only nine annual changes, the results are interpreted solely as exploratory diagnostics of timing and co-movement. They are not evidence that one variable caused another.

Table 4. Selected first-difference Spearman co-movement diagnostics, 2015–2023

Indicator A	Indicator B	Spearman ρ	p value	Interpretation
EV sales growth	Electricity-demand growth	0.733	0.025	Exploratory; N=9 annual changes
EV sales-share change	HHI change	−0.733	0.025	Exploratory; N=9 annual changes
EV sales-share change	Charger growth	−0.733	0.025	Exploratory; N=9 annual changes
Electricity-demand growth	Oil-displacement growth	0.817	0.007	Exploratory; N=9 annual changes
EV sales growth	Oil-displacement growth	0.550	0.125	Exploratory; N=9 annual changes
HHI change	Charger growth	0.533	0.139	Exploratory; N=9 annual changes

Note. Approximate two-tailed p values are shown only as descriptive diagnostics. The coefficients do not identify causality or provide confirmatory evidence.
Source: authors' calculations from International Energy Agency (2024).

The positive co-movement between EV sales growth and electricity-demand growth ($\rho = 0.733$) and between electricity-demand growth and oil-displacement growth ($\rho = 0.817$) is directionally consistent with system consequences expected during EV expansion. The negative co-movement between EV sales-share change and HHI change ($\rho = -0.733$) indicates that years with larger penetration gains tended to coincide with declines in concentration in this short window.

The negative association between EV sales-share change and charger growth must not be read as evidence that charging infrastructure reduced EV adoption or vice versa. It simply shows that the annual rates did not move in lockstep during the nine observed changes. From a CI perspective, this is precisely why market, structure, infrastructure, and transition indicators should remain separate monitoring signals rather than being collapsed into a single index.

4.5 Scenario-foresight intelligence

Signal. Under STEPS, passenger-EV sales are approximately 11.01 million in 2025, 17.93 million in 2030, and 22.17 million in 2035. APS gives approximately 10.93 million, 17.61 million, and 22.16 million. Both scenarios report passenger-EV sales shares of 49% in 2025, 68% in 2030, and 85% in 2035. These are conditional scenario records, not observed outcomes.

Scenario stability versus sensitivity. The 2035 market-penetration conclusion is stable across STEPS and APS, but the technology mix is not equally stable. The reported 2035 BEV sales are 20.0 million under both scenarios; PHEV sales are 2.1 million under STEPS and 1.8 million under APS; FCEV sales are 70,000 under STEPS and 360,000 under APS. The corresponding scenario-sensitivity measure is 0% for BEV, –15.38% for PHEV, and 134.88% for FCEV.

Strategic meaning. Agreement between scenarios can be treated as a stronger planning signal than disagreement. Conversely, high divergence is itself informative: it identifies assumptions that should be monitored and areas in which flexibility may be more valuable than irreversible commitment. Scenario foresight is therefore used to identify exposure to alternative pathways rather than to claim which pathway will occur.

Table 5. Technology-segment intelligence and 2035 scenario comparison

Technology	2023 sales	2023 share %	Recent CAGR %	2035 STEPS	2035 APS	Scenario sensitivity %
BEV	5,400,000	66.662	80.39	20,000,000	20,000,000	0.00
PHEV	2,700,000	33.331	130.66	2,100,000	1,800,000	–15.38
FCEV	520	0.006	423.15	70,000	360,000	134.88

Note. Recent CAGR uses 2020–2023 for BEV/PHEV and 2021–2023 for FCEV because of its very small base. Scenario sensitivity is (APS–STEPS) divided by the mean of their absolute values, ×100. Source: authors' calculations from International Energy Agency (2024).

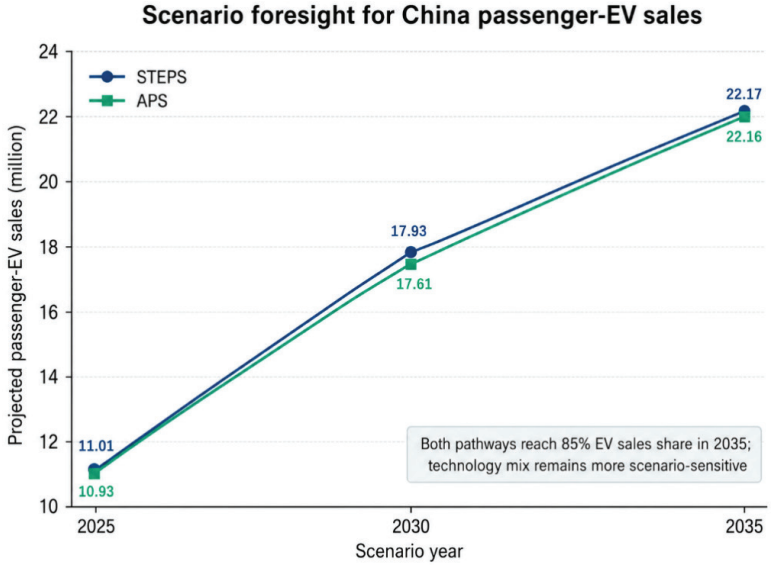

Figure 5. Scenario foresight for China passenger-EV sales under STEPS and APS.

Source: authors' calculations from International Energy Agency (2024). The 2025, 2030, and 2035 points are conditional scenario outputs and should not be interpreted as realized observations.

4.6 Sustainable CI decision support, feedback, and robustness

The Sustainable Competitive Intelligence contribution lies in how the signals are combined without collapsing their meaning. Market penetration indicates scale; HHI and entropy indicate internal technology structure; charger intensity indicates a macro ecosystem pressure signal; and scenario divergence indicates future uncertainty. Each signal therefore supports a different decision question and a different monitoring cadence.

The framework translates these signals into four bounded decision verbs: scale, transition, monitor, and hedge. These are analytical heuristics rather than investment recommendations. "Scale" applies when evidence is large and comparatively stable; "transition" applies when the composition of opportunity is changing; "monitor" applies where current scale is small or assumptions are uncertain; and "hedge" applies where infrastructure or technology assumptions could materially alter exposure. The purpose is to connect evidence to a revisable decision category, not to produce a universal ranking.

The feedback loop is what converts one-time market analysis into Sustainable Competitive Intelligence. Actual outcomes should be compared with prior expectations; deviations should trigger review of assumptions; new source vintages should update the signal set; and lessons should be retained for later decisions. This continuous cycle supports organizational learning and strategic resilience, which are the mechanisms through which repeated intelligence use may contribute to sustainable competitive advantage (Olaleye et al., 2023; Olszak et al., 2023).

Table 6. Robustness checks and bounded strategic decision translation

Object / check	Primary evidence	Alternative / decision category	Strategic interpretation
EV-sales growth window	2014–2023 CAGR = 68.75%	2018–2023 CAGR = 49.35%	Rapid growth conclusion remains
2023 concentration	HHI incl. FCEV = 0.555	HHI excl. FCEV = 0.556	No substantive change
Infrastructure denominator	115.19 / 1,000 total road EVs	123.85 / 1,000 passenger EVs	Macro readiness interpretation stable
2035 penetration	STEPS sales share = 85%	APS sales share = 85%	High penetration is scenario-stable
FCEV option value	STEPS 2035 = 70,000	APS 2035 = 360,000	Monitor; high scenario divergence
BEV decision signal	Large 2023 scale; 20m in both 2035 scenarios	Scale / defend	Capacity, cost, differentiation, ecosystem
PHEV decision signal	33.33% of 2023 EV sales; high recent growth	Transition / optimize	Portfolio coverage; avoid indefinite extrapolation
Charging decision signal	2.70m public points; stock-adjusted ratio non-monotonic	Readiness / hedge	Track absolute scale and denominator-adjusted load

Note. Decision categories are analytical heuristics, not investment recommendations. Robustness asks whether the central intelligence interpretation changes under a reasonable alternative operational choice.

5. FINAL CONSIDERATIONS

5.1 Contributions and implications

Using the predefined 2010–2023 observation window, this study frames evidence from China's passenger-EV market as a bounded Sustainable Competitive Intelligence problem. The empirical results show rapid market growth through 2023, a post-2021 shift toward a larger PHEV share, substantial expansion of public charging infrastructure, and variation in market shares and technology mixes across conditional scenario outputs associated with different levels of market penetration. These conclusions are based on a retrospective assessment and should not be interpreted as evidence of current market conditions, firm-level competitive dynamics, causal relationships in consumer behavior, or deterministic future outcomes.

The methodological contribution lies in separating four analytical layers—market, competitive structure, ecosystem readiness, and scenario foresight—using transparent measures suited to a short annual time series. The 2023 HHI is calculated directly rather than inferred from the trend, and its interpretation is consistent throughout: a larger HHI indicates greater concentration.

A higher normalized entropy corresponds to higher balance in technology stocks, as it was interpreted in Figure 4. The proposed capability logic for SCI is theoretical: Capability indicators from the public marketplace are not used as measures of an organization's CI capability. Instead, they provide inputs to a planning–sensing–analysis–dissemination–utilization–governance–feedback process. This process can be repeated to contribute to the learning and resilience of the organization, thus giving a conceptual connection to sustainable strategic decision-making and sustainable competitive advantage. This formulation conveys the relevance of the study within the sustainable competitive intelligence framework, while at the same time remaining within the empirical bounds of the available information.

5.2 Limitations and future research

The study has a limited time frame and source vintage restriction. The empirical results reflect this time period up to 31 December 2023 and do not reflect the actual market situation in 2024 or 2025. The STEPS and APS records from 2025 are model output and not observations, and thus are not suitable for filling this temporal gap.

The local download date of Global EV Data 2024 was not captured, which makes it difficult to precisely reconstruct the provenance; but the provenance data source release, analytical cut-off, evidence categories, filters, and records downloaded are present to help reproduce the data. Future updates must rely on a single more up-to-date IEA data vintage and re-establish the entire analytical framework, not incorporate individual more recent observations to previous analytical series.

Second, evidence is national and technology-segment based. No identification of manufacturer, brand, model, price, product introduction, patent, distribution or firm strategy. Firm-level competitor intelligence and the firm-specific competitive advantage are thus not included in the empirical analysis. Third, national aggregation conceals provincial, urban, and network heterogeneity in

adoption, charging access, income, policy implementation, and infrastructure utilization. More granular geographic evidence would improve local competitive and ecosystem analysis.

Fourth, the study is descriptive and associational. The first-difference screen contains only N = 9 annual changes and is used solely for exploratory co-movement diagnostics. No causal effect of policy, charging infrastructure, prices, fuel costs, or technology change is identified.

Fifth, the infrastructure measures are macro indicators. Public charger counts and stock-adjusted intensity do not measure private charging, utilization, reliability, spatial access, charging power, or queueing. Site-level decisions require more detailed operational data.

Sixth, STEPS and APS are conditional scenario outputs rather than probability distributions or statistical forecasts. Scenario disagreement is interpreted as strategic uncertainty, not as an error term or a significance test.

Future work can extend the framework vertically to brand- and product-level competition, horizontally to provincial or city markets, and temporally to higher-frequency data. A complementary organizational survey could also test the capability layer—planning, sensing, analysis, dissemination, utilization, feedback, governance, learning, resilience, sustainable decision-making, and sustainable competitive advantage—using genuine respondent data collected under an appropriate ethics and sampling protocol.

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Ethics Statement: Not applicable. The empirical study uses aggregate public secondary market data and does not analyze human-participant responses or personal data.

Declaration of AI-Assisted Use: The authors used OpenAI ChatGPT for English-language editing, structural organization, drafting assistance, formula verification, and manuscript-level consistency checking of derived values, tables, and figures. The tool was not used to generate or replace empirical market observations or respondent evidence. All empirical claims remain tied to the stated IEA source fields and formulas, and the authors retain full responsibility for the accuracy, integrity, and originality of the final manuscript.

Data Availability: The empirical analysis uses the China passenger-car subset of the International Energy Agency Global EV Data 2024 release described in Section 3.1. The analysis was conducted on an archived fixed-vintage extract with an analytical cut-off of 31 December 2023. Observed passenger-EV indicators cover 2010–2023 and public charging infrastructure covers 2014–2023, whereas records for 2025, 2030, and 2035 are retained only as conditional STEPS/APS scenario outputs. The exact local download date of the archived file was not preserved and is therefore reported as unavailable rather than reconstructed. The source release is identified as International Energy Agency (2024), Global EV Outlook 2024 / Global EV Data 2024. Reproduction of the historical analysis should preserve the same evidence categories, filters, variable definitions, and formulas. A current-state extension should instead use one newer documented source vintage and rerun all raw and derived indicators, figures, tables, correlations, and robustness checks.

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