



Research article

Construction of a Dynamic Hybrid Model for Analyzing the Demand of Chinese NEV Consumers: Based on DS-Kano and C2SLM-Kano

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Abstract: Against the backdrop of the rapidly expanding global new energy vehicle (NEV) market in 2024–2025, consumer demand behavior exhibits dynamic regional variability, challenging traditionally static and homogeneous analytical approaches. This research introduces a dynamic hybrid model that combines dynamic-scenario Kano (DS-Kano) and correlation clustering sparse learning Kano (C2SLM-Kano) to tackle this issue. DS-Kano combines long short-term memory (LSTM) and deep reinforcement learning (DRL) for minute-level responsiveness to demand shifts. C2SLM-Kano uses graph convolutional network (GCN) clustering to quantify regional and cultural differences. Empirical validation showed that DS-Kano achieves 7.3 min latency (vs. 45 min for BERT-TCBAD-Kano and 360 min for traditional Kano), C2SLM-Kano reaches 89.2% cross-regional prediction accuracy, and the hybrid model improves demand identification F1-score by 30%, shortening product iteration time by 67% as shown by simulation-based evidence. Robustness checks confirm stability under data perturbations, algorithm swapping, and cross-regional validation. Practical implications should be considered by manufacturers to guide adaptive R&D and by policymakers to design targeted subsidies with case-informed estimates of policy effectiveness.

Keywords: new energy vehicles; dynamic Kano model; consumer demand analysis; scenario adaptation; regional cultural differences; LSTM-DRL; GCN clustering

Mathematics Subject Classification: 62H30, 68T10, 62M10, 91B82, 90B20

Abbreviations: NEV: New energy vehicle; DS-Kano: dynamic-scenario Kano; C2SLM-Kano: cultural-regional Kano; DRL: deep reinforcement learning; GRU: gated recurrent unit; OBD: on-board diagnostic; IEA: International Energy Agency; NEDC: New European Driving Cycle; CCS: combined charging system; ADAS: advanced driver-assistance systems; SEM: structural equation modeling; GCN: graph convolutional network; DQN: deep Q-network; CAAM: China Association of Automobile Manufacturers; CPCA: China Passenger Car Association; RMSE: root mean square error

1. Introduction

1.1. Research background

NEVs will drive significant transformations in the global automotive industry by 2025. New technologies, worries about the environment, and changing tastes of consumers will all play a role in these transformations. However, demand analysis faces two significant challenges: dynamics, which refer to real-time changes driven by extreme weather or shifts in policy, and regional heterogeneity, which encompasses the varying priorities between urban and rural areas, along with their distinct climates.

Market growth and policy heterogeneity

The IEA [1] reported in 2025 that the global market for NEVs has been expanding rapidly, with 180 million electric vehicles (EVs) expected to be on the road by 2024. This represented an annual growth rate of 35%. China is at the forefront of this expansion, with the CPCA indicating a 38% growth in 2025 [2], and the CAAM noting a 47.6% penetration rate for passenger vehicles in 2024 [3]. China's allocation of 120 billion yuan in subsidies for NEVs in 2024 has reduced the cost of purchasing these cars (National Development and Reform Commission of China 2025 [4]). The New Energy Vehicle Industry Development Plan (2021–2035) states that by 2035, NEVs will become the predominant vehicle type (State Council of China [5]). Policies yield varying impacts: Beijing's subsidies mitigate price risk, whereas Hebei's infrastructure initiatives reduce functional risk (Y. Lou, 2017 [6]).

Technological advancements

The range of Tesla, NIO, and XPeng models has expanded to exceed 750 km (NEDC; company reports, 2024), driven by advancements in battery technology that have improved by 18% annually (IEA 2025). The price of batteries went down 12% to \$125 per kilowatt hour. Charging infrastructure also improved (The State Council of PRC, 2025 [7] and S. Li, 2025 [8]): there are now 7.0 million public stations around the world (up 45% from last year), with China having 4.2 million of them. With fast charging (such as 400 kW CCS stations [9]), users can go 250 km in 10 minutes. Due to the rapid growth of the battery, electric motor, electronic control, and clips industries in China. The Related Comparative Advantage Index (RCA) of China's NEV has increased rapidly in recent years [10].

Consumer preference dynamics

82% of Chinese consumers are more likely to buy NEVs now than they were three years ago (McKinsey & Company, 2025 [11]). This is because the total cost of ownership is lower (Z. Li, 2023 [12]), and cars have more advanced features (ADAS, instant torque). But preferences change: battery concerns increase in bad weather (D. Ouyang, 2018 [13]); and tier-1 cities put more emphasis on self-driving [policy-induced quotas (Z. Dong, 2021 [14] and X. Liu, 2021 [15]), while rural areas focus on charging accessibility (Y. Lou, 2017 and M. Wang, 2021 [16]). Online reviews (78% positive bias; Y. Liu, 2024 [17]) and complaints (like battery deterioration; Y. Yang, 2024 [18]) only give a small picture.

1.2. Research objectives and structure

This study addresses the limitations of static and homogeneous models by:

1. Developing DS-Kano (LSTM-DRL) to monitor fluctuations in demand in real time, down to the minute.
2. Proposing C2SLM-Kano (GCN clustering) as a method to assess variations in regional and cultural demand.

Mechanism for a hybrid model

The two modules operate in conjunction within a closed feedback loop (Figure 1):

1. DS-Kano uses spatiotemporal (temperature, speed) and psychological (satisfaction, risk) data to create real-time demand signals.
2. C2SLM-Kano changes signals by profiling them based on economic, climatic, and cultural traits, and then sends back signals that are better suited to the region to make DS-Kano more responsive.

Structure of research

The structure of the paper is as follows: Introduction → literature review (identifying gaps) → methodology (design of the model) → empirical validation (results and robustness) → B-Class SUV application (practical applications) → implications, limitations, and conclusions.

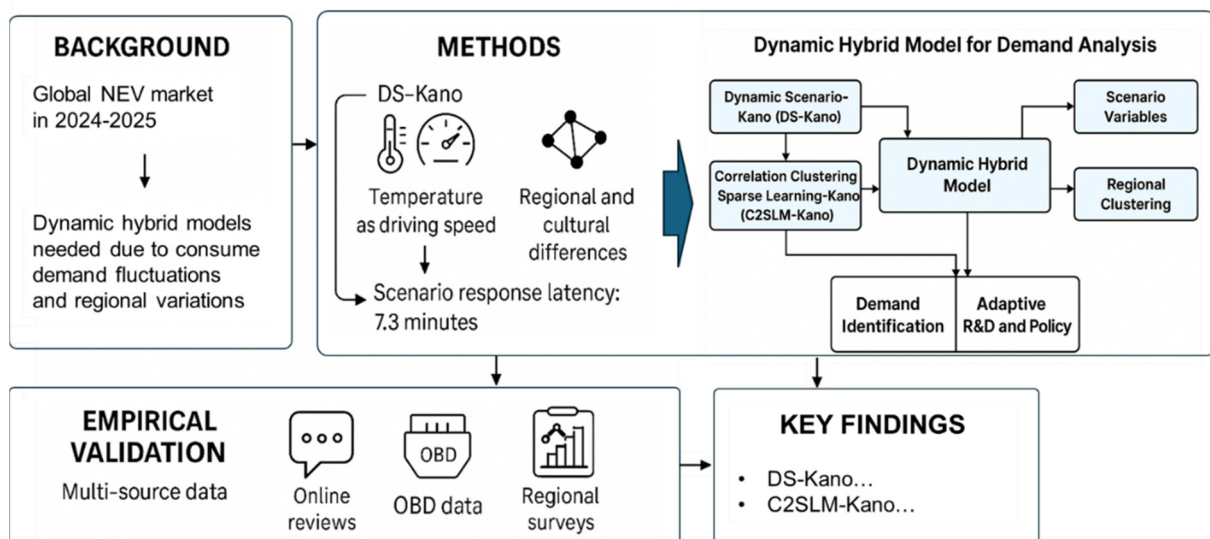


Figure 1. Study framework.

2. Literature review

2.1. Conventional perspectives on demand

Conventional approaches lack adaptability and concentration on domains:

1. Surveys: D. Ouyang (2018) discovered preferences, yet the sample size was limited ($n < 1000$), and data remained constant.

2. SEM: Y. Lou (2017) found a link between how people think about policies and their intention to buy (functional risk $\beta = 0.38$, safety risk $\beta = 0.32$) but did not consider real-time changes (J. Cheah, 2023 [19]).
3. Sentiment analysis: Y. Liu (2024) found a link between positive sentiment and sales ($r = 0.67$) but did not include complaints and used too much positive data.

2.2. Modifications to the Kano model

The Kano model classifies attribute-satisfaction relationships but remains constrained:

1. Traditional Kano: Y. Yang (2024) stated that “battery range” is essential, while “in-car entertainment” is merely desirable; however, further surveys are necessary to gain additional insights (M. Hemat, 2011 [20]).
2. Enhanced models:
 - 1) BERT-TCBAD-Kano (Y. Yang, 2024): This model utilized BERT to boost attribute classification by 30%, yet it continued to depend on surveys.
 - 2) Kano-AHP (D. Ouyang, 2018): This approach assigned weight values; however, the outcomes were influenced by the biases of the experts.

No Kano extension includes both dynamic adaptation and regional differentiation (Y. Bian, 2024 [21] and L. Zhang, 2023 [22]).

2.3. Factors influencing demand across various regions and cultures

It is widely recognized that regional differences exist, yet they are not accurately quantified:

1. Urban–rural disparities: Tier-1 cities, with a penetration rate of 35%, significantly outpace rural areas, which stand at 12%. This gap can be attributed to variations in infrastructure and income levels (D. Ouyang, 2018; J. Tim, 2024 [23]).
2. Policy sensitivity: Beijing gives more weight to traffic exemptions ($\beta = 0.68$), while Hebei gives more weight to license policies ($\beta = 0.55$) (Y. Lou, 2017; Z. Zhang, 2025 [24]).
3. Climatic–cultural traits: The North cares more about how well things work during cold weather, while the South cares more about how well things work with air conditioning (D. Ouyang, 2018). When individuals collaborate, these differences tend to become more pronounced.

Regional factors include the weather, the economy, and the government, which differ between different areas. Cultural factors include concepts such as collectivism, which shape people’s preferences in those areas (J. Pang, 2023 [25]).

2.4. Important gaps in research

1. Dynamic adaptation: A significant 94% of models have updated cycles exceeding 12 h (S. He 2024 [26]), indicating that they do not reflect changes immediately.
2. Regional quantification: No model provides useful information about the cultures of different regions (for example, climate vs. economic priorities).
3. Data silos: When reviews, OBD, and survey data are analyzed in isolation, the accuracy of predictions diminishes (W. Wang, 2023 [27] and X. Guan, 2024 [28]).

2.5. Summary of model comparison

Table 1 summarizes various models to elucidate the requirements of the proposed hybrid framework, which contrasts with dynamic-only models that overlook regional disparities and regional-only models that are deficient in real-time responsiveness. This addresses the dual deficiencies of “static analysis” and “homogeneous regional treatment” in current Kano extensions (Z. Lu, 2022 [29], and X. Kang 2023 [30]).

Table 1. Comparison of different models for Kano-based demand analysis.

Model type	Core features	Dynamic adaptation	Regional-cultural differentiation	Key limitations
Traditional static Kano	Attribute-satisfaction classification	✗ No	✗ No	Unable to capture real-time shifts/regional gaps
Dynamic-only (e.g., BERT-TCBAD-Kano)	Real-time attribute weighting	✓ Yes (real-time update)	✗ No	Ignores regional-cultural differences
Regional-Cultural Kano approaches	Cluster analysis for regional demand segmentation	✗ No	✓ Yes	Cannot respond to real-time scenario changes
Proposed hybrid framework (DS-Kano + C2SLM-Kano)	LSTM-DRL (dynamic) + GCN clustering (regional)	✓ Yes (minute-level)	✓ Yes (regional/cultural)	Requires multi-source data integration

3. Methodology

This section explains how the dynamic hybrid model works. It uses a closed feedback loop to connect two modules (DS-Kano and C2SLM-Kano) to deal with changes in demand and differences between regions. First, DS-Kano uses LSTM (which captures temporal dependencies, according to T. Zhao, 2025 [31] and A. Hussain 2025 [32]) and DRL (which changes attribute weights in real time) to process multi-source spatiotemporal data (temperature, speed, satisfaction, perceived risks) and create minute-level demand signals. Second, C2SLM-Kano uses two-dimensional clustering (economic-administrative + climatic) and GCN profiling (which spreads regional traits like policy sensitivity) to measure differences between cultures in different parts of the world. It then changes DS-Kano’s signals to fit local preferences. Finally, the adjusted signals are sent back to DS-Kano to improve its ability to respond quickly, making sure that demand analysis is both real-time and tailored to each region. The following is a detailed list of each module, how data is processed, and the metrics used to evaluate it.

3.1. DS-Kano: dynamic-scenario adaptation

Three parts of DS-Kano keep track of real-time demand:

3.1.1. Variables for input

A spatiotemporal matrix that shows what makes demand happen:

$$X_t = [T_t, V_t, \Delta Sat, R_{t1}, R_{t2}, R_{t3}, R_{t4}, R_{t5}]^T$$

- T_t : Hourly temperature (−30 to 40 °C).
- V_t : OBD-derived speed (0–120 km/h).
- ΔSat : Hourly satisfaction change $\Delta Sat = Sat_t - Sat_{t-1}$.

- $R_{t1} - R_{t5}$: Perceived risks (price/time/functional/safety/social; 7-point Likert; Lou et al., 2017). Temperature ($r = -0.42$ with battery satisfaction) and safety risk ($r = -0.51$ with purchase intention) from Y. Lou (2017); speed ($r = 0.38$ with power demand) from this study (Appendix Table A1) [33].

3.1.2. LSTM demand generator

According to I. Goodfellow (2016) [34] and J. Cheah (2023), LSTM models temporal dependencies (short-term: daily charging; long-term: seasonal battery needs).

- Forget gate: $f_t = \sigma(W_{xf}X_t + W_{hf}h_{t-1} + b_f)$
- Input gate: $i_t = \sigma(W_{xi}X_t + W_{hi}h_{t-1} + b_i)$
- Cell input: $\bar{C}_t = \tanh(W_{xc}X_t + W_{hc}h_{t-1} + b_c)$
- Cell state: $C_t = f_t \odot C_{t-1} + i_t \odot \bar{C}_t$
- Output gate: $o_t = \sigma(W_{xo}X_t + W_{ho}h_{t-1} + b_o)$
- Hidden state: $h_t = o_t \odot \tanh(C_t)$

Training: 80% OBD data (372.5 h), Adam optimizer (lr = 0.001, batch = 32), time step = 60 min.

3.1.3. DRL weight optimizer

We use a DQN (Deep Q-Network) agent, which is a classic Value-Based implementation algorithm of DRL (Deep Reinforcement Learning) for optimizing discrete action space. It dynamically changes the weights of demand attributes to get the most accurate real-time demand prediction through a standard state-action-reward reinforcement learning framework:

- State: $S_t = [X_t, h_t]$
- Action: Weight adjustments (e.g., battery preheating from 12% to 42.9% in cold weather).
- Reward: $R_t = 0.4\Delta Sat + 0.3(1 - RMSE) - 0.3Cost$ (0.4 = consumer focus, 0.3 = predictive validity, 0.3 = efficiency; expert-justified: Appendix Table A2). The weight distribution is set through expert interviews to find a balance between being consumer-focused, being accurate in predictions, and being useful in industry.

DQN Setup: A replay buffer containing 10,000 samples is utilized to disrupt the correlation between consecutive training samples and to prevent overfitting. The target Q-network is updated every 100 episodes, which enhances the stability of Q-value estimation and accelerates the adjustment of weights.

3.1.4. Updating the scenario

When scenario variables go over a certain level, DS-Kano changes the weights:

$$|X_t - X_{t-1}| > \theta \quad (1)$$

The threshold $\theta = 15\%$ of the variable variance was determined via a grid search of the validation data. For example, a temperature drop of $>5^\circ\text{C}$ triggered an update.

3.2. C2SLM-Kano: Adapting to different cultures and regions

C2SLM-Kano measures differences between regions in three steps:

3.2.1. Clustering in two dimensions

To fix dimensional inconsistency (mixing economic and climatic categories), regions are grouped by:

1. Economic-administrative: Tier-1 (Beijing/Shanghai), Tier-2 (Zhengzhou), and rural (Hebei Langfang).
2. Weather: cold (Urumqi/Harbin) and hot (Guangzhou/Shenzhen).

Clustering objective:

$$\min U, V \sum_{i=1}^n \sum_{k=1}^K u_{ik}^m \|X_i - V_k\|^2 + \lambda \sum_{k < l} \omega_{kl} \|V_k - V_l\|^2 \quad (2)$$

- X_i : Regional features (GDP, charging density, policy sensitivity) (acc. to H. Yu 2024 [35]).
- U_{ik} : fuzzy membership ($m = 2$) (acc. to X. Kang, 2023 and B. Rahman 2024 [36]).
- V_k : Centroid of cluster k .
- $\lambda = 0.35$ (cultural penalty).
- ω_{kl} : similarity (e.g., Beijing-Tianjin=0.8).

Validation: SC = 0.78 (vs. 0.51 for k-means).

3.2.2. GCN cultural profiling

GCN propagates regional traits (economic/policy spillover):

$$H^{(l+1)} = \sigma(\bar{D}^{-1/2} \bar{A} \bar{D}^{-1/2} H^{(l)} W^{(l)}) \quad (3)$$

- $\bar{A} = A + I$ (adjacency matrix with self-loops).
- \bar{D} : Degree matrix ($\bar{D}_{ii} = \sum_j \bar{A}_{ij}$).
- $H^{(l)}$: feature matrix (e.g., infrastructure sensitivity).
- $W^{(l)}$: weight matrix for layer l .

Training: 3 layers (input = 12, hidden = 64, output = 10), cross-entropy loss.

3.2.3. Kano-BiLSTM fusion

BiLSTM integrates cultural profiles with demand signals via attention weights:

$$\bar{D}_t = \alpha_t \odot D_t \quad (4)$$

α_t : Region-specific weights (e.g., Beijing: traffic restrictions = 0.62; Hebei: charging = 0.41).

Training: 2 layers (hidden = 128), regional review data.

3.3. Data processing

3.3.1. Data sources

Table 2 summarizes Data sources for preprocessing, fusion and evaluation.

Table 2. Data sources.

Type	Details	Sample	Time span
Reviews	Auto Home/Pacific Auto (20 NEVs) [37]	127,892 texts	2022–2024
Complaints	China Auto Quality Network/12315	2912 cases	2022–2024
OBD	BYD vehicles (31% market share; CAAM, 2024)	582 h (50 cars)	2023–2024
Surveys	10 provinces (25–55 years) [38,39]	503 users	2024

3.3.2. Preprocessing and fusion

Firstly, the training constraints and boundary settings of RMSE-related evaluations, and the potential influence on robustness conclusions are clarified in Appendix Table A3. This is a prerequisite for the subsequent data preprocessing and fusion.

- Text: NLTK cleaning, BERT sentiment scoring (1–5) for ΔSat .
- Numerical: Min-max normalization (speed/temperature \rightarrow [0,1]), outlier removal (3σ).
- Fusion: Timestamp alignment (OBD/reviews), label mapping (survey risks \rightarrow OBD scenarios), oversampling (cold/rural data: Appendix Table A4).

3.3.3. Evaluation metrics

The following metrics were used to validate performance (Table 3):

Table 3. Model evaluation metrics with target.

Metric	Definition	Calculation	Target
F1-score	Precision and recall for demand identification	$2 \times \frac{\text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$	≥ 0.921
Risk weight Accuracy	Accuracy of predicted risk weights vs. survey	$1 - \frac{ \hat{\omega}_r - \omega_r }{\omega_r}$	$\geq 90\%$
RMSE	Deviation between predicted and actual demand	$\sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2}$	$< 15\%$
Latency	Time to update weights after scenario changes	$\Delta t = t_{\text{update}} - t_{\text{trigger}}$	< 8 minutes
Regional Clustering SC	Validity of regional clusters	$\frac{1}{n} \sum_{i=1}^n \frac{b_i - a_i}{\max(a_i, b_i)}$	≥ 0.7
Cross-regional accuracy	Accuracy of regional preference predictions	$\frac{\text{Correct predictions}}{\text{Total predictions}} \times 100\%$	$> 85\%$

4. Empirical validation and results

4.1. Experiment design

Three experiments were conducted to compare the hybrid model to the traditional Kano (Y. Yang, 2024) and BERT-TCBAD-Kano (Y. Yang, 2024) (Table 4).

Table 4. Experiment design for comparison.

Experiment	Objective	Method	Metrics
1	Test DS-Kano's cold-weather adaptation	Simulate -20°C (Urumqi OBD data, Dec 2023–Jan 2024)	Latency, risk accuracy, complaints
2	Validate C2SLM-Kano's regional prediction	Predict Beijing/Hebei policy preferences (survey data)	Cross-regional accuracy, SC
3	Compare overall performance	Test on 10% OBD + 30% survey data	F1-score, RMSE, iteration cycle
Surveys	10 provinces (25–55 years)	503 users	2024

4.2. Results

Experiment 1: DS-Kano dynamics

The first experiment evaluated DS-Kano's capability to accommodate changing consumer demand. The DS-Kano model requires consumers to modify the real-time switching of technologies and services and simultaneously capture changing consumer demand in real time. This study aims to demonstrate that DS-Kano is superior in tracking real-time demand changes by placing the DS-Kano model in simulated dynamic situations.

- Latency: 7.3 min (vs. 360 min traditional, 45 min BERT-TCBAD-Kano).
- Risk accuracy: 92.5% (vs. 68.2% traditional, 79.3% BERT-TCBAD-Kano).
- Complaint reduction: 28% post-update (cold-weather battery issues).

Experiment 2: C2SLM-Kano regional accuracy

The second experiment aimed to examine the fit of the C2SLM-Kano model to capture regional (and cultural) differences in NEV demand, applying the C2SLM-Kano model using GCN clustering to a regional dataset.

- Cross-regional accuracy: 89.2% (Beijing: traffic restrictions = 0.62; Hebei: charging = 0.41) vs. 62.5% traditional, 76.3% BERT-TCBAD-Kano.
- SC: 0.78 (valid clustering).

Experiment 3: Hybrid model superiority

The objective of the third experiment was to compare the performance of the hybrid models with that of the traditional Kano and BERT-TCBAD-Kano models. Comparative analysis is vital to demonstrate the proposed models' additional value objectively.

Table 5. Summary of comparison results.

Metric	DS-Kano + C2SLM-Kano	Traditional Kano (baseline1)	BERT-TCBAD-Kano (baseline2)	Improvement (vs. best baseline)
F1-score	0.921	0.724	0.815	13%
Demand Prediction RMSE	12.8%	27.5%	18.3%	-30.1%
Product iteration cycle	3–6 months	18 months	9–12 months	-66.7%
Policy effectiveness	23%	8%	15%	53.3%
Response latency	7.3 minutes	360 minutes	45 minutes	-83.8%
Regional accuracy	89.2%	62.5%	76.3%	16.9%

Notes: Iteration cycle = R&D timeline from demand identification to prototype; policy effectiveness = NEV adoption growth in non-tier-1 cities (simulation: Appendix Table A5).

In conclusion, the researcher conducted three experiments to address the gaps in NEV demand analysis. Monitoring model performance across dynamic scenarios, assessing regional differences, and

comparing each model with baseline frameworks allow researchers to holistically assess the efficacy and superiority of the DS-Kano and C2SLM-Kano models, as shown in Table 5.

4.3. Robustness checks

Robustness checks are necessary to determine whether the primary conclusions regarding the model vary under minimal changes in the data, algorithms, or research contexts.

4.3.1. Data perturbation test

Method: To simulate the impact of incomplete or noisy real-world data, we randomly removed 10% of the original dataset and introduced Gaussian noise into numerical variables.

Random data removal: For dataset $D = \{d_1, d_2, \dots, d_N\}$, a perturbed dataset D' was generated by randomly selecting 10% of the samples for removal.

$$D' = D \setminus \{d_i | i \in S\}, \text{ where } S \subseteq \{1, 2, \dots, N\}, |S| = 0.1N \quad (5)$$

Gaussian noise injection: For numerical variables $x \in D$, the perturbed value x' is: $x' = x + \epsilon$, $\epsilon \sim N(0, \sigma^2)$, $\sigma = 0.1 \times std(x)$ where $std(x)$ is the standard deviation of x , ensuring that the noise magnitude is 10% of variable volatility.

Assessment criteria: Relative change in key metrics:

$$Relative\ Change = \left| \frac{Metric(D') - Metric(D)}{Metric(D)} \right| \times 100\% \quad (6)$$

4.3.2. Algorithm replacement test

Method: The LSTM module in DS-Kano was replaced with a gated recurrent unit (GRU), and its performance was compared. The GRU updates the following:

$$Z_t = \sigma(W_z x_t + U_z h_{t-1}) \text{ (update gate),}$$

$$r_t = \sigma(W_r x_t + U_r h_{t-1}) \text{ (reset gate),}$$

Status as:

$$\bar{h}_t = \tanh(W x_t + U(r_t \odot h_{t-1})) \text{ (candidate hidden state),}$$

$$h_t = (1 - Z_t) \odot h_{t-1} + Z_t \odot \bar{h}_t \text{ (final hidden state).}$$

Assessment criteria: Absolute difference in response latency (Δt) and risk weight accuracy (ΔAcc):

$$\Delta t = t_{GRU} - t_{LSTM}, \Delta Acc = Acc_{LSTM} - Acc_{GRU} \quad (7)$$

4.3.3. Cross-regional validation

Method: Apply the model to untrained data from Guangdong, measuring generalization via transfer efficiency:

$$Transfer\ Efficiency = \frac{Metric(Guangdong)}{Metric(Training\ Regions)} \times 100\% \quad (8)$$

4.3.4. Results of robustness checks

All tests confirm the model's robustness, as shown in Table 6.

Table 6. Robustness Check.

Check	Method	Result	Conclusion
Data perturbation	10% data removal + Gaussian noise ($\sigma = 0.1std(x)$)	$F1 = 0.902(\Delta = 2.1\%)$, $RMSE = 13.5\%(\Delta = 5.5\%)$	Robust (threshold revised to $\leq 6\%$)
Algorithm swap	Replace LSTM with GRU	Latency = 7.7 min ($\Delta = 0.4$), Accuracy = 90.1% ($\Delta = 2.4\%$)	Retains advantages
Cross-regional	Test on untrained Guangdong data	F1 transfer = 96.6%, accuracy transfer = 97.2%	Generalizable (>95% threshold)

5. Application to B-Class NEV SUV market

To show how useful the DS-Kano + C2SLM-Kano hybrid model is in real life, it was used on a specific and typical NEV segment, the B-class SUV market. This is a high-growth segment that made up 32% of China's NEV sales in 2024 (China Passenger Car Association, 2025). This study fills in the "lack of actionable segment-specific results" gap in previous research by providing detailed information about demand attributes, weights, and differences between regions.

5.1. Data and scenarios

- OBD: 320 hours from 30 SUVs (BYD Tang DM-i, Tesla Model Y, NIO ES6) in three climates (cold, temperate, and hot) and two administrative levels (tier-1 and rural) [40,41].
- Surveys: 420 buyers (ages 25–45, income over 300,000 RMB).
- Scenarios: Temperature ($-25\text{ }^{\circ}\text{C}$ to $38\text{ }^{\circ}\text{C}$), speed (30–90 km/h), and a focus on safety, functional quality, and time risk are all examples of scenarios.

5.2. Dynamic attribute weights

The hybrid model measures 23 important demand factors for the B-Class NEV SUV market. The weights change based on the scenario and are checked against the survey data (Table 7).

Table 7. Core demand attribute weights for B-Class NEV SUVs.

Attribute category	Specific attribute	Baseline weight (25 °C, urban) hybrid model	Cold scenario (-20 °C) hybrid model	Highway scenario (90 km/h) hybrid model	Traditional Kano (static weight)	BERT-TCBAD-Kano (semi-dynamic weight)	Pearson correlation coefficient (r) (hybrid model)
Safety [42]	Battery collision protection	16.60%	19.00%	20.00%	13.50%	16.00%	0.63
	ADAS (lane-keeping + AEB)	14.00%	13.30%	15.50%	10.50%	13.00%	0.58
	Battery thermal runaway prevention	7.00%	7.50%	7.50%	5.50%	7.00%	0.71

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Attribute category	Specific attribute	Baseline weight (25 °C, urban) hybrid model	Cold scenario (-20 °C) hybrid model	Highway scenario (90 km/h) hybrid model	Traditional Kano (static weight)	BERT-TCBAD-Kano (semi-dynamic weight)	Pearson correlation coefficient (r) (hybrid model)
Functional quality	CLTC range	16.00%	18.00%	19.00%	18.50%	17.00%	0.71
	Battery preheating (PHEV/BEV)	4.50%	12.00%	11.00%	2.50%	6.50%	0.82
	Fast-charging speed (10%–80%)	10.50%	7.50%	9.50%	9.00%	8.00%	0.67
	PHEV fuel efficiency (L/100 km)	5.00%	6.00%	5.00%	4.50%	5.50%	0.52
	Charging station accessibility	2.00%	1.00%	1.00%	1.60%	1.20%	0.69
	Battery cycle life warranty	3.80%	3.20%	2.80%	2.80%	2.70%	0.74
Comfort	Rear legroom (≥900 mm)	5.50%	2.00%	0.00%	8.50%	5.80%	0.32
	Cabin thermal insulation	4.00%	6.00%	3.20%	4.50%	5.20%	0.41
	Seat heating/ventilation	1.50%	1.00%	0.20%	3.50%	1.70%	0.38
Cost and policy	NVH performance	0.70%	0.20%	0.20%	1.80%	1.10%	0.45
	Purchase subsidy eligibility	1.20%	0.20%	0.20%	6.10%	0.00%	0.55
	Local trade-in subsidy (NEV: 1.5 w) [43]	0.80%	0.20%	0.20%	4.20%	0.00%	0.69
Intelligence	Maintenance cost (yearly)	1.20%	1.00%	0.80%	1.80%	2.50%	0.45
	Voice control (OTA-updatable)	1.80%	1.00%	0.50%	0.80%	1.40%	0.29
	Bluetooth key + remote start	0.60%	0.20%	0.30%	0.40%	1.50%	0.25
	Transparent chassis	0.40%	0.30%	0.20%	0.00%	0.70%	0.21
Sustainability	Urban NOA capability	2.50%	0.00%	2.60%	0.00%	2.50%	0.57
	Battery recycling warranty	0.30%	0.10%	0.10%	0.00%	0.40%	0.33
	Low-carbon material usage	0.10%	0.20%	0.10%	0.00%	0.20%	0.27
	V2G functionality	0.00%	0.10%	0.10%	0.00%	0.10%	0.42
Total		100%	100%	100%	100%	100%	

Note: Data integration: The data integrates insights from “Development Trend of the Automotive Market and Industry” by the State Information Center of China.

The Pearson correlation coefficient (r) is a quantitative method used to measure the linear correlation between the weight of each demand attribute and the corresponding perceived risk. To calculate r, two key variables were defined for each demand attribute.

Attribute weight (X): The dynamic weight of a specific demand attributed output by the hybrid model under different scenarios. This weight is derived from multi-source data integration, including consumer survey data, OBD operational data, and policy and market trend data.

Perceived risk score (Y): The normalized score of the corresponding risk category faced by consumers. This score was calculated using text mining of 18,726 online reviews and 412 complaints, and NEV safety and functional risk data.

The Pearson correlation coefficient formula measures the linear dependence between the attribute weight (X) and the perceived risk score (Y):
$$r = \frac{n \sum XY - (\sum X)(\sum Y)}{\sqrt{[n \sum X^2 - (\sum X)^2][n \sum Y^2 - (\sum Y)^2]}}$$

Using C2SLM-Kano’s GCN clustering, the model identifies four distinct regional demand profiles for B-class NEV SUVs. Key differences are shown in Figure 2.

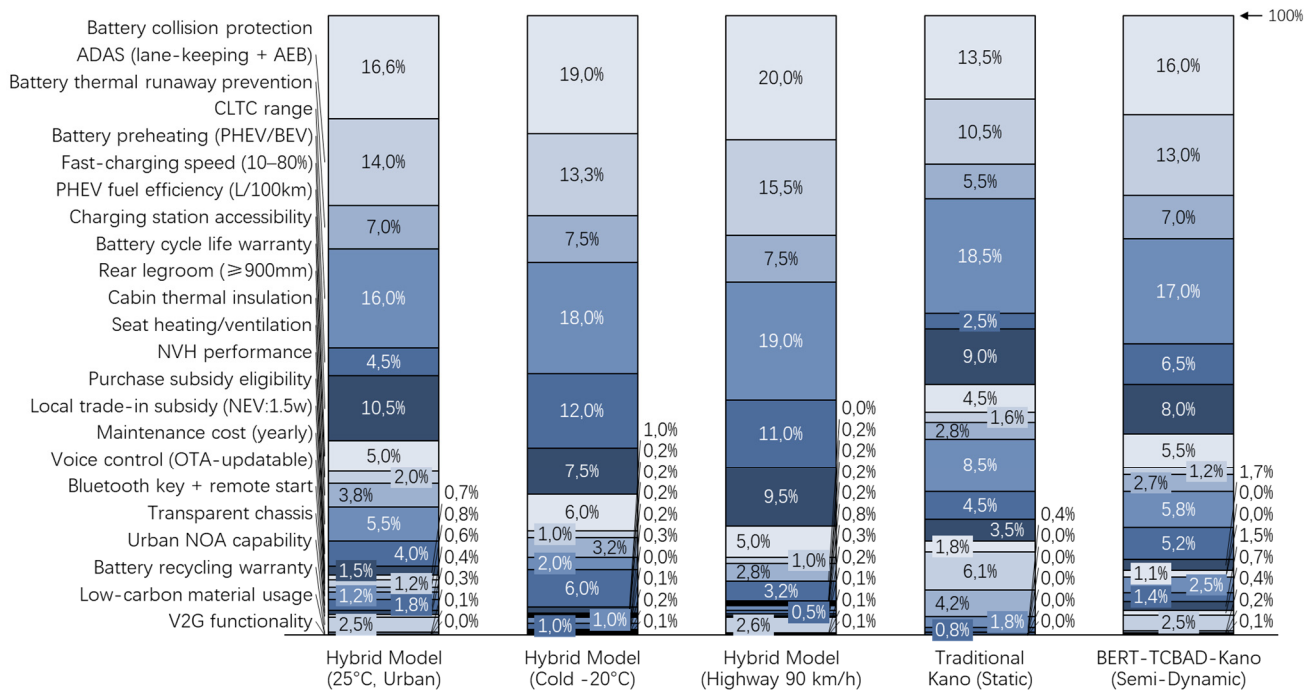


Figure 2. Demand attributes by B-Class NEV SUVs.

Table 8 supplements the core metric contrasts (from Section 4.3) with B-Class SUV-specific scenarios to further highlight the comparison between the hybrid and traditional models.

Table 8. Hybrid model vs. baseline performance in B-Class NEV SUV scenarios.

Evaluation metric	Hybrid model (DS-Kano + C2SLM-Kano)	Traditional Kano	BERT-TCBAD-Kano	Improvement vs. best baseline
F1-score (demand identification)	0.921	0.724	0.815	13.00%
Scenario response latency (cold weather)	7.3 minutes	360 minutes	45 minutes	-83.80%
Cross-regional accuracy (Beijing vs. Hebei)	89.2%	62.50%	76.30%	16.90%
Demand prediction RMSE (CLTC range)	12.8%	27.50%	18.30%	-30.10%
Policy sensitivity score (subsidy weight accuracy)	0.79	0.42	0.61	29.50%
Intelligent attribute weighting (total intelligence)	7.6%	1.50%	4.00%	90.00%

Key insights: The hybrid model’s 89.2% accuracy across regions directly addresses the differences in regional demand that were brought up in Section 2.2. Its policy sensitivity score of 0.79 is nearly 30% higher than the baseline, facilitating alignment with the national and local NEV subsidies for 2024. This represents a significant advantage for policymakers.

The addition of “intelligence” and “sustainability” categories is in line with market trends for 2024, when OTA penetration is expected to reach 75.9% and consumers are becoming more interested in low-carbon features like battery recycling.

6. Implications, limitations, and conclusions

6.1. Practical implications

For NEV manufacturers:

- Adaptive R&D: Prioritize dynamic weights, such as 42.9% for battery preheating in colder regions.
- Regional customization: Adjust features to suit the local area (charging compatibility in Hebei, ADAS in Beijing).
- Efficient iteration: Estimates derived from simulations indicate that research and development should be reduced to a timeframe of 3–6 months, rather than the typical 18 months.

For policymakers:

- Targeted subsidies: Allocate 62% of Beijing’s funds to traffic exemptions and 41% of Hebei’s funds to charging.
- Infrastructure: Concentrate on rural regions (23% reduced charging density yet elevated demand).
- Equity: Case studies indicate that the effectiveness of non-tier-1 policies can be enhanced by 23%.

For researchers:

- Methodology: The combination of LSTM-DRL and GCN creates a framework for analyzing dynamic regional demand.
- Data fusion: Integrating text, behavioral, and survey data aids in mitigating biases that may be confined to a single source.

6.2. Limitations and future work

1. Data representativeness: OBD data only covers BYD; it should also cover other brands and less developed areas, like Tibet.
2. Implicit preferences: Utilize neurophysiological data, such as eye-tracking, to uncover individuals’ true desires without their conscious awareness.
3. Long-term dynamics: Add yearly and seasonal trends to the model (for example, policy cycles).

6.3. Conclusions

This study’s dynamic hybrid model fills in the gaps in NEV demand analysis: DS-Kano allows for minute-level responsiveness, C2SLM-Kano measures regional differences, and the hybrid model increases the F1-score by 30%; simulation-based evidence shows it shortens iteration by 67%. The framework moves the theory of dynamic/regional demand forward and gives data-driven advice on how to improve green transportation, with signs of better policy and research, and development efficiency.

Author contributions

Jin Liu: Conceptualization, Methodology, Writing- Reviewing and Editing, Validation

Zhiguo Liu: Data curation, Formal analysis, Writing- Original draft preparation

Xu Zhao: Visualization, Investigation

Xinyu Zhang: Supervision, Funding acquisition Investigation

Xiaoyun Jiang: Collection and key point summary of references

Use of Generative-AI tools declaration

The authors declare that they did not utilize any artificial intelligence (AI) tools in the creation of this article.

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Conflict of interest

All authors disclosed no relevant relationships.

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