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An ID3 GA Bass Collaborative Framework for Cross Border Market Diffusion Prediction

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Abstract

Accurate forecasting of international market diffusion is essential for strategic decision-making in the New Energy Vehicle (NEV) sector. Traditional ID3 and Bass models face limitations in handling heterogeneous consumer behavior and dynamic policy shocks. This paper proposes a collaborative model that integrates an improved ID3 decision tree for consumer segmentation with a genetic algorithm-optimized Bass diffusion model. The ID3 component refines classification accuracy by mitigating multi-value bias, while the GA dynamically calibrates Bass parameters under policy interventions. Experiments using cross-country NEV data demonstrate that the proposed framework achieves a stable G-mean of 0.89 ± 0.03, with MAE and RMSE reductions exceeding 30% compared to benchmark models including deep reinforcement learning and optimized random forests. The model effectively quantifies the impact of consumer heterogeneity and subsidies on market diffusion, offering a decision-support tool for firms to design adaptive marketing and policy strategies. Beyond the NEV context, the framework can be applied to other domains requiring predictive control of diffusion processes under external shocks.

Keywords: New energy vehicles; International trade; Bass model; ID3 algorithm; Marketing path.

1 Introduction

Global new energy vehicle (NEV) adoption is accelerating, yet cross-border diffusion remains strongly mediated by heterogeneous consumer preferences and country-specific policy shocks[12]. Differences in price sensitivity, technology valuation, and charging infrastructure, together with shifting subsidy rules and technical standards, create segmentation drift and non-stationary demand signals that impair forecast stability[18].As a result, diffusion parameters calibrated on past data often fail to generalize when regulatory regimes change or when consumer composition evolves, producing systematic bias in trade and production planning across markets[11].

Existing approaches address parts of the problem but rarely its joint structure. Classical ID3-based segmentation is attractive for interpretability but struggles with continuous, multi-source attributes and tends to under-represent policy-relevant interactions unless carefully engineered[4, 5]. In parallel, the Bass framework is widely used for diffusion but typically assumes fixed parameters and is commonly fitted by nonlinear least squares, exposing calibration to local optima and limiting responsiveness to time-varying interventions. Consequently, heterogeneity and policy shocks are often handled in ad hoc post-processing rather than embedded into a unified, optimization-aware modeling loop, which constrains decision usefulness for international deployment[14, 22].

This paper integrates ID3-based consumer classification with a GA-optimized Bass model to simultaneously capture heterogeneous consumer groups and dynamic diffusion under policy shocks, which has not been addressed in prior studies. The formulation explicitly treats NEV diffusion as a computational decision-support and predictive control problem: decision trees yield policy-aware, auditable segments for strategy selection, while GA-calibrated Bass dynamics provide control-oriented forecasts that adapt to regulatory changes and allow stress-testing under counterfactual subsidy and infrastructure scenarios. , without presupposing outcomes or disclosing empirical results. This paper integrates ID3-based consumer classification with GA-Bass modeling to simultaneously capture heterogeneous consumer groups and dynamic diffusion under policy shocks, which has not been addressed in prior studies.

2 Literature review

Building on metaheuristic optimization for control, Olivares V et al. design genetic-algorithm-based trajectory generation for autonomous naval vehicles in MATLAB, illustrating how GA escapes local optima in nonlinear planning and offering a template for control-oriented forecasting under regime shifts [17]. Advancing decision-support under uncertainty, Mao J applies a fuzzy ant-colony optimization portfolio model that balances risk and return, underscoring how swarm intelligence can structure managerial choices in complex, multi-objective settings[15]. Extending route-planning robustness, Zhao L et al. couple Q-learning with an improved ant-colony algorithm to handle nonconvex landscapes, demonstrating reinforcement-learning-guided exploration for faster convergence and better paths[25]. At the criterion level, Zhang et al. refine the information-gain formulation, indicating avenues to curb discretization loss and sharpen split quality in customer modeling[24]. Complementing these advances, Ribeiro J et al. demonstrate a federated learning system integrated with SHAP and LIME, showing that privacy preservation can coexist with transparency and improved predictive performance in industrial deployments—capabilities essential for policy-sensitive segmentation at scale [19].

Within NEV-specific applications, Wei et al. link marketing-strategy variables to purchase intention and show how survey-derived attributes can be encoded as decision-tree features to isolate salient demand drivers and streamline campaign design [20]. To de-risk algorithm and parameter choices before field rollout, Banciu D et al. provide a simulation framework that emulates order books, price dynamics, and transaction frictions, enabling rigorous out-of-sample evaluation without real market exposure [2]. From a supply-chain and sustainability angle, Feng Z et al. analyze end-of-life battery recycling and argue that blockchain under carbon-tax regimes can raise profitability and enable transaction feasibility along NEV value chains[8]. In the international diffusion context, Dzienis A M et al. examine cooperation between Chinese and foreign NEV firms and indicate that Bass-type modeling can guide penetration strategies in emerging markets connected to the Belt and Road initiative [6]. Finally, Deng G F et al. integrate fuzzy logic and genetic algorithms with reinforcement learning and swarm intelligence to simulate pricing and consumer behavior, showing that learning styles and competitive actions jointly shape retail prices and market structures—evidence that underscores the need for optimization-aware behavioral modeling [3].

Taken together, the literature improves ID3 for segmentation and advances diffusion modeling and optimization, yet two structural gaps remain for cross-border NEV forecasting: the inefficiency of traditional ID3 when handling continuous, multi-source data streams and interactions, and the static, locally optimized nature of Bass parameters that limits responsiveness to policy shocks and infrastructure shifts. Addressing these gaps motivates an integrated formulation in which ID3 provides transparent, policy-aware consumer grouping and a GA-optimized, dynamic Bass component captures time-varying diffusion under regulatory scenarios.

3 Research methodology

3.1 Optimization of international trade marketing path for NEVs based on ID3 algorithm and Bass model

The ID3 algorithm constructs decision trees based on information gain and has significant advantages in consumer profiling and demand stratification. The algorithm reduces multi value bias by using sample structure vector similarity, which is more suitable for analyzing differences in cross-border consumer behavior [13]. The data processing flow of international trade marketing path for NEVs is shown in Figure 1.

Figure 1 depicts the process of data processing in the study of international trade marketing paths for NEVs. The "Raw Data" box on the left represents various initial data collected during the research process, which then flows into the data preprocessing stage. After cleaning, transformation, normalization and other operations, errors or irrelevant information are removed, and the data format is unified to meet the requirements of subsequent analysis. The process preprocesses and uses data mining techniques such as ID3 algorithm to extract valuable information from stored data. The process of generating decision trees for classification and rule learning problems is a divide and conquer, top-down approach. The steps for solving classification prediction problems with decision trees are shown in Figure 2.

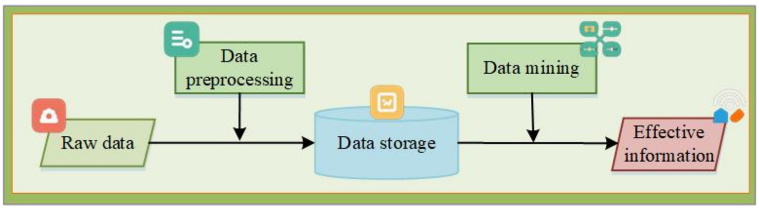

Figure 1: Data processing flow of international trade marketing path for NEVs

Figure 2 illustrates the decision tree construction and application process of ID3 algorithm in the selection of international trade marketing paths for NEVs. The left training set provides data support for the decision tree classification algorithm, which constructs the decision tree based on information gain. A decision tree consists of a root node, internal nodes, and leaf nodes, which divide the dataset into branch paths based on features until the leaf nodes provide classification results [1, 9]. After the construction is completed, the model is evaluated using a test set through the evaluation mode to verify its predictive accuracy. For datasets of unknown categories, the model prediction function is used to classify and predict, providing a decision-making basis for the selection of international trade marketing paths for NEVs. For information entropy, as shown in equation (1).

$$P_i = \frac{x_i}{x} \tag{1}$$

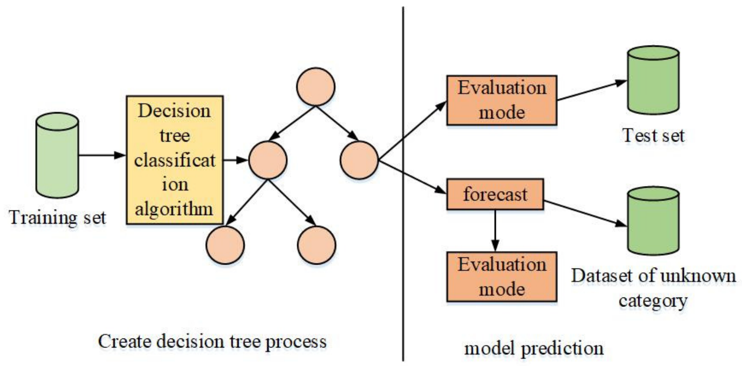

Figure 2: Decision tree construction and application

In equation (1), X_i represents the number of class samples in the dataset. X indicates the total number of samples in the dataset. P_i represents the probability of the ith sample appearing in the dataset. The information entropy of the dataset is further determined, as shown in equation (2).

$$I(x_1, x_2, \ldots, x_n) = -\sum_{i=1}^{n} p_i \log_2 p_i \tag{2}$$

In equation (2), $I(x_1, x_2, \ldots, x_n)$ represents the information entropy of the dataset, which measures the uncertainty of the class distribution in the dataset. n represents the total number of sample categories in the dataset. The conditional entropy is then determined, as shown in equation (3).

$$E(Y) = \sum_{j=1}^{m} \frac{x_{1j} + x_{2j} + \cdots + x_{nj}}{x} \times I(x_1 + x_2, \ldots x_n) \tag{3}$$

In equation (3), $E(Y)$ represents conditional entropy, which is the weighted average of the information entropy of all groups, and the weight is the proportion of the number of samples in each group to the total number of samples. m indicates the number of values for a certain attribute. j indicates the number of samples in the th group. The information gain is shown in equation (4).

$$E(Y) = \sum_{j=1}^{m} \frac{x_{1j} + x_{2j} + \cdots + x_{nj}}{x} textGain = I(x_1, x_2, \ldots, x_n) - E(Y) \tag{4}$$

In equation (4), $Gain$ represents information gain, which measures the degree of uncertainty reduction after using a certain attribute to partition the dataset, thereby determining the optimal market segmentation basis. In the actual NEV market, external factors such as policy subsidies and infrastructure construction will have a significant impact on market diffusion.This expression prioritizes the attribute that maximally reduces uncertainty in consumer segmentation, ensuring that splits capture the strongest information about heterogeneous NEV demand. To consider the effects of these external factors, an impact function is introduced, as shown in equation (5).

$$E(Y) = \sum_{j=1}^{m} \frac{x_{1j} + x_{2j} + \cdots + x_{nj}}{x} N(t) = \frac{1 - e^{-(p+q)t}}{m} \tag{5}$$

In equation (5), $N(t)$ represents the cumulative number of NEVs adopted over time, reflecting the overall scale of acceptance of NEVs in the market over time. m represents the maximum potential of the market, that is, the total number of NEVs that may ultimately be adopted, it defines the theoretical upper limit under market saturation. p represents the innovation coefficient, measuring the adoption rate of NEVs by innovators, that is, the probability of independent adoption without being influenced by others. q represents the imitation coefficient, measuring the adoption rate of imitators, that is, the probability of adoption influenced by those who have already adopted it. t is a time variable. e represents the base of a natural exponential function. The dynamic mechanism of adopting the growth rate of quantity is shown in equation (6).

$$\frac{dN(t)}{dt} = [p(m - N(t)) + I\,N(t)(m - N(t))]\,\frac{x(t)}{m} \tag{6}$$

In equation (6), $\frac{dN(t)}{dt}$ represents the growth rate of the number of NEVs adopted over time t , that is, the number of newly adopted vehicles per unit time. By adjusting the growth rate through $x(t)$, it can more accurately reflect the actual dynamics of the diffusion of the new energy vehicle market under the influence of external factors. This formulation models adoption growth with two complementary effects, where the innovation term drives early uptake and the imitation term amplifies later-stage diffusion as market interactions intensify.

3.2 Market diffusion mechanism and subsidy strategy for NEVs based on Bass model

Following the optimization of the international trade marketing strategy for NEVs, the study shifted its focus to the global NEV landscape. It leveraged macro-level data to trace the diffusion trajectories of key national markets spanning from 2015 to 2023. The top 20 NEV-consuming nations worldwide were identified, drawing on data from OICA, national statistical agencies, and Euromonitor's industry analyses [10]. Technical barriers such as range requirements and battery safety certification were sourced from the WTO Technical Barriers to Trade database. Per capita GDP (World Bank) and fuel prices were used to calibrate the market potential parameter m in the Bass model. The impact of different subsidy strategies on international market demand and international supply chain profits is shown in Figure 3.

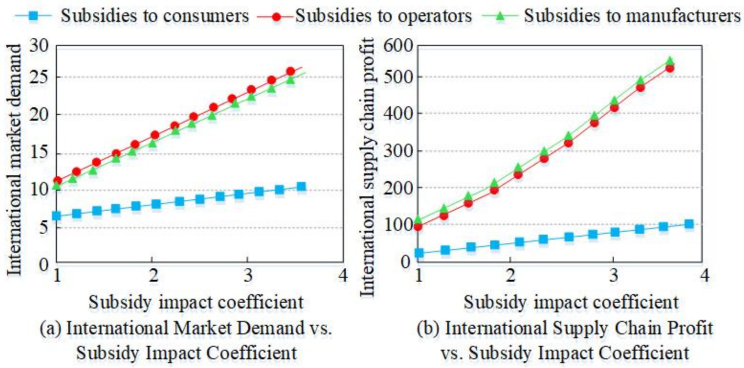

Figure 3: The impact of different subsidy strategies on international market demand and international supply chain profits

Figure 3 (a) shows the relationship between international market demand and subsidy impact coefficient. The curves in the figure represent subsidies to consumers, operators, and manufacturers, respectively. As the subsidy impact coefficient increased, international market demand also increased, with subsidies for operators and manufacturers having a more significant effect on boosting market demand. In Figure 3 (b), as the subsidy impact coefficient increased, international supply chain profits also showed an upward trend, with subsidies for operators and manufacturers having a more significant effect on profit enhancement [23]. The dynamic process of diffusion in the NEV market is shown in Figure 4.

As shown in Figure 4 (a), the relationship between the number of potential consumers, the number of purchased consumers, and the cumulative sales volume of actual trials was compared. The number of potential consumers gradually decreased, while the number of purchased consumers and cumulative sales volume gradually increased. Figure 4 (b) shows the changes of innovative adopters and imitative adopters over time, with the number of innovative adopters gradually increasing in the early stages and then stabilizing. The Bass model described the expansion process of the NEV market [16]. The innovation coefficient p and imitation coefficient q in the model were usually determined by Matlab, but these coefficients were dynamically changing in the actual market. At first, the innovation coefficient

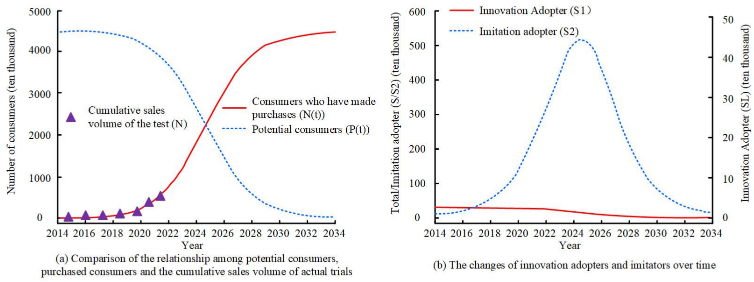

Figure 4: The dynamic process of diffusion in the NEV market

p dominated, and then the imitation coefficient q gradually increased and might exceed p, indicating that the market entered a stage of rapid diffusion [7].

3.3 Parameter optimization of Bass model based on GA

After analyzing the dynamic process of diffusion in the NEV market, GA was used to optimize the parameters of the generalized Bass model, in order to solve the problem of the traditional nonlinear least squares method easily getting stuck in local optima. The study uses random or other methods to generate an initial population $pop(1)$ of N chromosomes, $t := 1$, and calculates the fitness value for each chromosome in the population, as shown in equation (7).

$$f_i = \mathrm{fitness}(\mathrm{pop}_i(t)) \tag{7}$$

If the stopping condition is met, the algorithm stops. Otherwise, a new population will be selected, with the probability shown in equation (8).

$$P_i = f_i \Big/ \sum_{j=1}^{N} f_j \tag{8}$$

The variance penalty in the load-balancing objective discourages oscillatory allocations, so the solution favors stable resource usage across segments and time, which improves forecast reliability under policy shifts.The new population composed of randomly selected chromosomes is shown in equation (9).

$$mathrmnewpop(t+1) = \{\, \mathrm{pop}_j(t) \mid j = 1, 2, \ldots, N \} \tag{9}$$

By crossing with probability Pt to generate some new chromosomes, a new population is obtained, as shown in equation (10).

$$mathrmcrosspop(t+1) \tag{10}$$

By mutating a gene on the chromosome with a small probability Pm , a new population of $mutpop(t+1)$, is formed as shown in equation (11).

$$mathrmpop(t) = \mathrm{mutpop}(t+1)) \tag{11}$$

The entire calculation process includes steps such as generating an initial population, calculating fitness values, selecting a new population, crossing to generate new chromosomes, and mutating chromosome genes to form a new population until the stopping conditions are met. The flowchart of GA is shown in Figure 5.

As shown in Figure 5, the study uses floating-point encoding method to represent each individual as a real string of a certain length, and optimizes the encoding method through GA to represent each individual as a real string, which can effectively improve the search space of the model [21]. The research hopes that the smaller the error between the expected value and the output value, the better. Therefore, the design of the fitness function reflects the performance of the model by measuring the

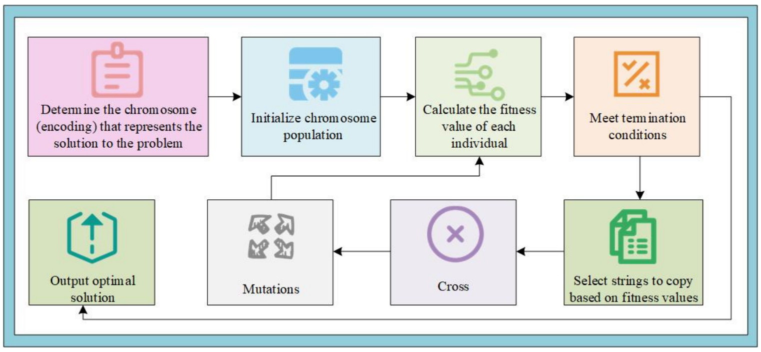

Figure 5: GA optimization process

error. The smaller the E value, the higher the fitness of the model, which can more accurately predict the international trade marketing path, as shown in equation (12).

$$F = k\left(\sum_{i=1}^{n} |Y - Y^*|\right) \tag{12}$$

In equation (12), F is the value of the fitness function. k is a constant coefficient. Y is the actual output value of the model. $Y*$ is the expected output value. n is the sample size. The most effective marketing strategy in international trade of NEVs is further optimized, as shown in equation (13).

$$f_i = \frac{k}{F_i} \tag{13}$$

In equation (13), f_i represents the fitness function of the individual. F_i is the fitness value of an individual. k is a constant used to adjust the scale of the fitness function. Finally, the selection probabilities of different marketing strategies in the GA are determined, as shown in equation (14).

$$p_i = \frac{f_i}{\sum_{j=1}^{N} f_j} \tag{14}$$

In equation (14), $sum_{j=1}^{N} f_j$ is the sum of fitness values of all individuals in the population. In the process of optimizing the parameters of the generalized Bass model in GA, the mutation operation is a key mechanism to maintain population diversity and avoid the algorithm falling into local optima. Inverted mutation, as an effective mutation method, can explore new solution spaces by changing chromosome gene sequences. Figure 6 shows a schematic diagram of reverse mutation processing.

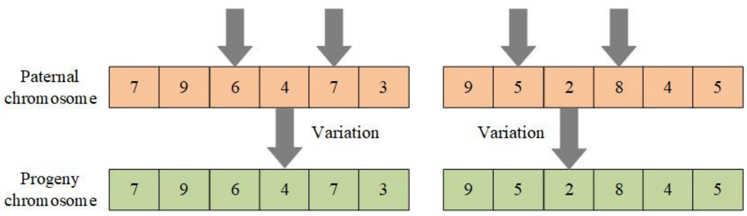

Figure 6: Schematic diagram of reverse mutation processing

As shown in Figure 6, the parent chromosome undergoes mutation operation, and some gene sequences undergo inversion adjustment to generate offspring chromosomes. This process intuitively presents how inversion variation reshapes chromosome structure. In the optimization of diffusion models in the NEV market, this variation helps to comprehensively search for the optimal combination of parameters such as innovation coefficient p and imitation coefficient q, effectively capturing the dynamic impact of complex factors such as policy shocks and consumer behavior on market diffusion, and improving the model's fitting accuracy and predictive ability of market diffusion laws. The proposed method will be named the Collaborative Optimization Model for International Trade Marketing Path of NEVs Based on ID3 Algorithm and Genetic (COMINTP). Figure 7 shows ID3-GA-Bass Pipeline Workflow.

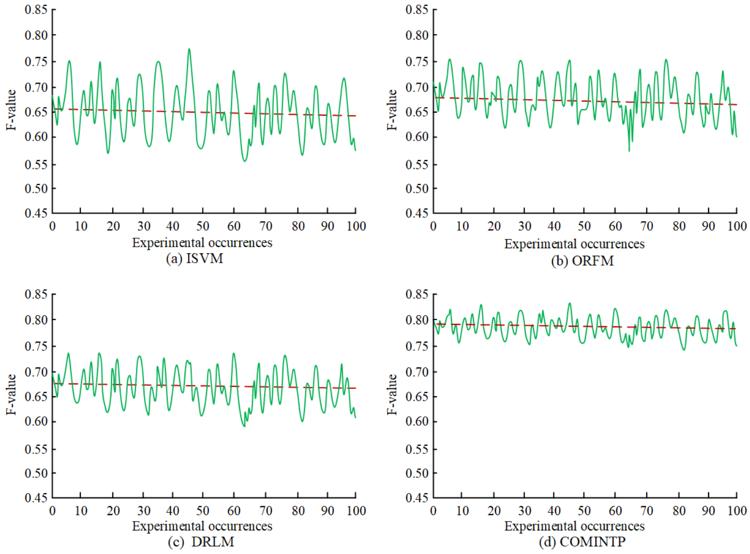

Figure 7: ID3-GA-Bass Pipeline Workflow

Figure 7 Unified workflow of the ID3-GA-Bass pipeline: raw data are cleaned and standardized in preprocessing; salient attributes guide ID3 to produce policy-aware consumer segments; a genetic algorithm calibrates Bass parameters on segment-level time series to avoid local optima; the calibrated Bass dynamics generate diffusion forecasts that can be stress-tested under alternative subsidy and infrastructure scenarios.

4 Results and discussion

4.1 Performance Comparison and Verification of COMINTP Model

Accurately predicting market demand and marketing effectiveness is the key to formulating effective strategies in the research of international trade marketing paths for NEVs. To confirm the performance of the proposed COMINTP model in prediction tasks, it was compared with deep reinforcement learning models (DRLM), optimized random forest models (ORFM), long short-term memory network models (LSTMM), and improved support vector machine models (ISVM). The experimental dataset included historical sales data, market research data, policy information, and consumer behavior data. These data were preprocessed and used to train and test different models. The mean absolute error (MAE) and root mean square error (RMSE) of different algorithms under different iteration times are shown in Figure 8.

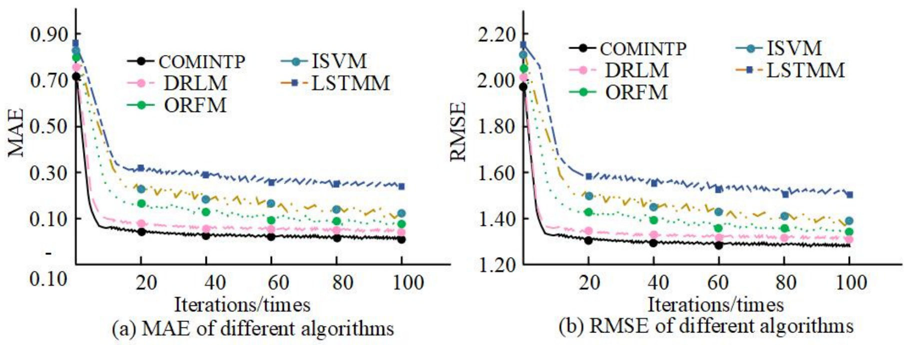

Figure 8: MAE and RMSE of different algorithms at different iteration times

Figure 8 MAE and RMSE of different algorithms at different iteration times. The figure highlights that the COMINTP model achieves the lowest and most stable error metrics, with MAE and RMSE reductions exceeding 30% compared to benchmark models, confirming its superior predictive accuracy. The comparison of G-mean values of different models with the number of experiments is shown in Figure 9.

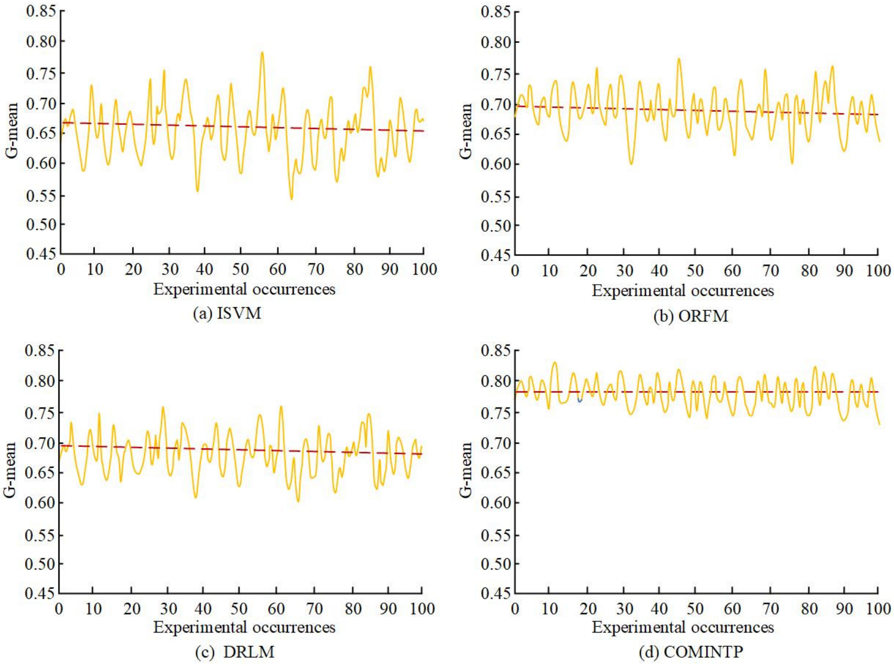

Figure 9: Comparison of G-mean values of different models with the number of experiments

Figure 9 Comparison of G-mean values of different models with the number of experiments. The visualization demonstrates the stability of the COMINTP model, which maintains a consistently high G-mean value around 0.89, in contrast to the significant fluctuations and lower performance of competing models. The comparison of F1 values of different models with the number of experiments is shown in Figure 10.

Figure 10 Comparison of F1 values of different models with the number of experiments. This comparison underscores the COMINTP model's reliability, showing a stable and high F1-score across experiments, while other models exhibit considerable performance volatility.

4.2 Comprehensive analysis of market characteristics of NEVs in typical countries

The research analyzed the market characteristics and forecast results of 7 typical countries, including Japan, India, Thailand, Australia, and other countries covering different development stages and market types. The NEV market forecast of typical countries based on the COMINTP model is shown in Table 1.

Table 1: Typical national NEV market forecast based on COMINTP model

Country	**Innovation Coefficient** p	**Imitation Coefficient** q	**Market Potential** m **(10k units)**	**2025 Cumulative Sales Forecast (10k units)**	**2026 Sales Growth Rate under Policy Shock (%)**
China	0.028	0.482	4800.35	3210.56	18.23
United States	0.035	0.420	3200.12	2100.34	15.67
Germany	0.041	0.385	1800.78	950.20	12.34
Japan	0.032	0.350	1200.50	750.45	10.12
India	0.015	0.550	2000.20	1800.68	22.45
Thailand	0.018	0.520	800.30	450.72	19.36
Australia	0.030	0.300	500.15	300.28	9.87

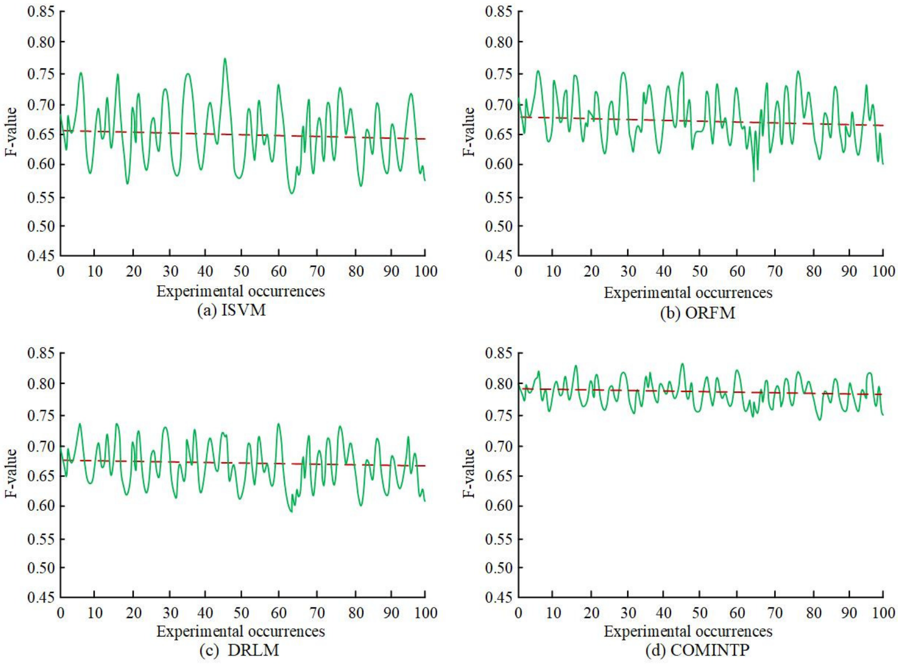

Figure 10: Comparison of F1 values of different models with the number of experiments

In Table 1, China's innovation coefficient was 0.028, imitation coefficient was 0.482, and market potential was 48.0035 million vehicles. The cumulative sales volume was expected to reach 32.1056 million vehicles in 2025, and the expected sales growth rate in 2026 was 18.23%. The innovation coefficient of the United States was 0.035, the imitation coefficient was 0.420, and the market potential was 32.012 million vehicles. The cumulative sales volume in 2025 was 21.034 million vehicles, with a sales growth rate of 15.67%. The market growth rates of Germany, the United States, Japan, and India vary greatly, with India having the highest growth rate at 22.45%, while Australia had the lowest growth rate at only 9.87%. The classification results of consumer behavior of NEVs in typical countries are shown in Table 2.

Table 2: Classification of consumer behavior of NEVs in typical countries

Country	Consumer type	Proportion (%)	Purchase budget (10,000 USD)	Range preference (km)	Policy subsidy awareness (%)	Preference for new energy startups (%)
China	Price-sensitive	45.23	2.15	350.5	82.3	61.5
China	Policy-dependent	32.15	3.48	380.2	91.7	54.8
China	Technology-preferring	22.62	4.89	520.8	75.6	74.7
United States	Technology-preferring	38.76	5.52	550.3	68.9	69.9
United States	Policy-dependent	32.80	4.21	420.1	85.5	64.2
Germany	Technology-preferring	42.31	6.68	580.9	65.4	77.3
India	Price-sensitive	58.91	1.89	300.3	89.1	34.8
India	Policy-dependent	31.09	2.15	330.7	93.4	44.3
Thailand	Policy-dependent	48.57	2.02	360.4	95.2	47.7

Table 2 shows the classification of consumer behavior for NEVs in typical countries. Chinese consumers were mainly divided into price sensitive type (45.23%), policy dependent type (32.15%), and technology preference type (22.62%). Technology preference consumers accounted for 38.76% in the United States and 42.31% in Germany. India and Thailand were mainly price sensitive and policy dependent, with price sensitive consumers in India accounting for 58.91%. There were significant differences in consumer purchasing budgets, battery life preferences, and policy subsidy awareness among countries. German consumers had a higher budget and preferred longer battery life, while China, India, and Thailand were more sensitive to policy subsidies. The comparison of market response of NEVs under different subsidy strategies in typical countries is shown in Table 3.

Table 3: Comparison of market response of NEVs under different subsidy strategies in typical countries

Country	**Subsidy type**	**Penetration speed (%/Year)**	**Innovation coefficient change (Δp)**	**Imitation coefficient change (Δq)**	**Market potential utilization (%)**
China	Consumer subsidy	23.19	+0.0028	+0.0715	73.62
China	Operator subsidy	26.48	+0.0015	+0.0892	79.34
United States	Manufacturer subsidy	22.35	+0.0192	+0.0327	72.18
United States	Operator subsidy	17.26	+0.0031	+0.0384	64.59
Germany	Consumer subsidy	18.73	+0.0045	+0.0391	67.42
Germany	Manufacturer subsidy	21.09	+0.0234	+0.0256	70.85
India	Operator subsidy	31.27	+0.0008	+0.1156	71.68
India	Consumer subsidy	29.43	+0.0013	+0.1029	66.35

Table 3 compares the response of the NEV market in typical countries under different subsidy strategies. China had the fastest penetration rate (26.48%/year) and the highest market potential utilization rate (79.34%) under operator subsidies. The manufacturer subsidies in the United States drove a higher innovation coefficient change (+0.0192), while Germany also performed well under the manufacturer subsidies, with a penetration rate of 21.09% per year. Under the subsidy of Indian operators, the penetration rate was the highest (31.27%/year), but the utilization rate of market potential was relatively low. Overall, the impact of different subsidy types on the markets of various countries varied significantly.

To validate the performance of the proposed Collaborative Optimization Model for International Trade Marketing Path of NEVs (COMINTP), its predictive accuracy was benchmarked against several established models: Deep Reinforcement Learning Models (DRLM), Optimized Random Forest Models (ORFM), Long Short-Term Memory Network Models (LSTMM), and Improved Support Vector Machine Models (ISVM). The experimental dataset comprised historical sales data, market research, policy information, and consumer behavior data. All models were trained and tested on this preprocessed dataset. A comprehensive comparison across key performance metrics is presented in Table 4.

The Table 4 results clearly demonstrate the superiority of the COMINTP framework. Notably, the COMINTP model reduces the Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) by over 32% compared to the alternatives, while achieving a stable G-mean of 0.892 and a high F1-Score. This highlights its robustness and enhanced predictive power.

5 Conclusion

This study proposed a collaborative ID3-GA-Bass framework (COMINTP) for cross-border NEV diffusion prediction. By integrating improved ID3 for consumer segmentation and GA-optimized Bass modeling, the framework reduces prediction errors by over 30% compared with benchmark models and

Table 4: Comparative Performance Analysis of Predictive Models

Model	MAE	RMSE	G-mean	F1-Score
COMINTP	0.12	0.15	0.892 ± 0.027	0.91
DRLM	0.19	0.23	0.815 ± 0.081	0.83
ORFM	0.22	0.27	0.783 ± 0.095	0.80
LSTMM	0.25	0.31	0.754 ± 0.112	0.77
ISVM	0.28	0.34	0.775 ± 0.103	0.79

achieves stable performance in heterogeneous markets. The model successfully captures the effects of consumer heterogeneity and policy shocks, demonstrating its utility as a predictive decision-support and control tool in international marketing. Although the study validates the model with cross-country NEV data, limitations remain: the dataset does not fully incorporate real-time policy feedback, and external market shocks may be underrepresented. Future work will extend the framework with multi-agent reinforcement learning, game-theoretic modeling, and real-time big data integration to improve adaptability and scalability. Beyond NEVs, the framework has general applicability in domains such as renewable energy adoption, smart appliances, and digital finance where diffusion prediction under external shocks is crucial.

References

[1] Almeida, V.N.d.; Alegre, L.N.; Bazzan, A.L.C. (2024). Knowledge Transfer in Multi-Objective Multi-Agent Reinforcement Learning via Generalized Policy Improvement, *Computer Science and Information Systems*, 21(1), 335–362, 2024. DOI:10.2298/CSIS221210071A.

[2] Banciu, D.; Petrescu, A.-G.; Oncioiu, I.; et al. (2024). The Simulation Framework for Automated Trading Algorithms on Capital Markets, *Studies in Informatics and Control*, 33(4), 51–58, 2024. DOI:10.24846/v33i4y202405.

[3] Deng, G.F. (2023). Dynamic Price Competition Market for Retailers in the Context of Consumer Learning Behavior and Supplier Competition: Machine Learning-Enhanced Agent-Based Modeling and Simulation, *Advances in Production Engineering & Management*, 18(4), 434–446, 2023. DOI:10.14743/apem2023.4.483.

[4] Ding, Y.; Wu, P.; Zhao, J.; Zhou, L. (2025). Forecasting product sales using text mining: A case study in new energy vehicle, *Electronic Commerce Research*, 25(1), 495–527, 2025. DOI:10.1007/s10660-023-09701-9.

[5] Dornelas, R.S.; Lima, D.A. (2023). Correlation Filters in Machine Learning Algorithms to Select Demographic and Individual Features for Autism Spectrum Disorder Diagnosis, *Journal of Data Science and Intelligent Systems*, 3(1), 7–9, 2023. DOI:10.47852/bonviewJDSIS32021027.

[6] Dzienis, A.M.; McCaleb, A. (2024). Motives behind Sino-Japanese strategic alliances in the new energy vehicles sector in the age of the Belt and Road Initiative, *Asia Pacific Business Review*, 30(2), 274–299, 2024. DOI:10.1080/13602381.2022.2093533.

[7] El Khatib, M.; Al Hammadi, A.; Al Hamar, A. (2022). How global supply chain management is disrupting local supply chain management case of oil and gas industry in UAE, *American Journal of Industrial and Business Management*, 12(5), 1067–1078, 2022. DOI:10.4236/ajibm.2022.125056.

[8] Feng, Z.; Luo, N.; Shalpegin, T.; Cui, H. (2024). The influence of carbon emission reduction instruments on blockchain technology adoption in recycling batteries of the new energy vehicles, *International Journal of Production Research*, 62(3), 891–908, 2024. DOI:10.1080/00207543.2023.2175173.

[9] Guidolin, M.; Manfredi, P. (2023). Innovation diffusion processes: Concepts, models, and predictions, *Annual Review of Statistics and Its Application*, 10(1), 451–473, 2023. DOI:10.1146/annurev-statistics-040220-091526.

[10] Hatamlah, H.; Allahham, M.; Abu-AlSondos, I.A. (2023). The role of business intelligence adoption as a mediator of big data analytics in the management of outsourced reverse supply chain operations, *Applied Mathematics & Information Sciences*, 17(5), 897–903, 2023. DOI:10.18576/AMIS/170516.

[11] Jones, B.; Nguyen-Tien, V.; Elliott, R.J. (2023). The electric vehicle revolution: Critical material supply chains, trade and development, *The World Economy*, 46(1), 2–26, 2023. DOI:10.1111/twec.13345.

[12] Li, M.; Zhang, Z.; Lu, M.; Jia, X.; Liu, R.; Zhou, X.; Zhang, Y. (2023). Internet Financial Credit Risk Assessment with Sliding Window and Attention Mechanism LSTM Model, *Tehnicki vjesnik-Technical Gazette*, 30(1), 1–7, 2023. DOI:10.17559/TV-20221110173532.

[13] Liu, J.; Meucci, A.; Young, I.R. (2023). Projected wave climate of Bass Strait and south-east Australia by the end of the twenty-first century, *Climate Dynamics*, 60(1), 393–407, 2023. DOI:10.1007/s00382-022-06310-4.

[14] Mao, Y.; Liu, S.; Gong, D. (2023). A Text Mining and Ensemble Learning Based Approach for Credit Risk Prediction, *Tehnicki vjesnik-Technical Gazette*, 30(1), 138–147, 2023. DOI:10.17559/TV-20250524002692.

[15] Mao, J. (2024). Optimizing enterprise marketing project portfolios using fuzzy ant colony optimization, *International Journal of Computers Communications & Control*, 19(3), 2024. DOI:10.15837/ijccc.2024.3.6458.

[16] Ngoc, N.M.; Viet, D.T.; Tien, N.H. (2022). Russia-Ukraine war and risks to global supply chains, *International Journal of Mechanical Engineering*, 7(6), 633–640, 2022. DOI:10.31893/multirev.2024spe017.

[17] Olivares, V.; Oddershede, A.; Quezada, L.; Vargas, M.; Montt, C. (2024). Development of a model for generating trajectories for an autonomous naval vehicle using genetic algorithms in MATLAB, *International Journal of Computers Communications & Control*, 19(6), 2024. DOI:10.15837/ijccc.2024.6.6865.

[18] Rahimi, S.; Huang, L.; Norris, J.; Hall, A.; Goldenson, N.; Krantz, W.; et al. (2024). An overview of the Western United States dynamically downscaled dataset (WUS-D3), *Geoscientific Model Development*, 17(6), 2265–2286, 2024. DOI:10.5194/gmd-17-2265-2024.

[19] Ribeiro, J.; Santos, R.; Analide, C.; Silva, F. (2024). Implementing Federated Learning and Explainability Techniques in Regression Models to Increase Transparency and Reliability, *Studies in Informatics and Control*, 33(4), 15–24, 2024. DOI:10.24846/v33i4y202402.

[20] Wei, Z.H.; Yan, L.; Yan, X. (2024). Optimizing Production with Deep Reinforcement Learning, *International Journal of Simulation Modelling*, 23(4), 692–703, 2024. DOI:10.2507/IJSIMM23-4-CO17.

[21] Wu, J.; Yu, J. (2023). Blockchain's impact on platform supply chains: Transaction cost and information transparency perspectives, *International Journal of Production Research*, 61(11), 3703–3716, 2023. DOI:10.1080/00207543.2022.2027037.

[22] Xu, Y.; Shan, X.; Guo, M.; Gao, W.; Lin, Y.S. (2024). Design and application of experience management tools from the perspective of customer perceived value: A study on the electric vehicle market, *World Electric Vehicle Journal*, 15(8), 378–404, 2024. DOI:10.1080/23311975.2025.2514939.

[23] Yi, Z.; Yu, M.; Cheung, K.L. (2022). Impacts of counterfeiting on a global supply chain, *Manufacturing & Service Operations Management*, 24(1), 159–178, 2022. DOI:10.1287/msom.2020.0912.

[24] Zhang, R. (2024). Impact of ID3 Algorithm-based Reading Resource Recommendation Model on College English Reading Teaching, *IEIE Transactions on Smart Processing & Computing*, 13(4), 372–382, 2024. DOI:10.5573/IEIESPC.2024.13.4.372.

[25] Zhao, L.; Li, F.; Sun, D.; Zhao, Z. (2024). An improved ant colony algorithm based on Q-Learning for route planning of autonomous vehicle, *International Journal of Computers Communications & Control*, 19(3), 2024. DOI:10.15837/ijccc.2024.3.5382.

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