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A Study on the Dynamic Interrelationship Mechanism of Factors Influencing New Energy Vehicle Purchase Intention Based on DEMATEL-FCM Theory

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KEYWORDS

New Energy Vehicles; Purchase Intention; Influencing Factors; DEMATEL-FCM Theory Model; Dynamic Correlation Mechanism; Consumer Behavior

ABSTRACT

Objective: Consumers' purchase decisions regarding new energy vehicles (NEVs) constitute a complex system, yet existing studies predominantly use static models that overlook the causal hierarchy and dynamic feedback among influencing factors. This study aims to fill this gap by developing an integrated model to systematically reveal the dynamic interrelationships affecting Chinese consumers' willingness to purchase NEVs. Methods: Employing a mixed-methods design, this study surveyed 728 residents in Zhengzhou, China. First, the Decision-Making Trial and Evaluation Laboratory (DEMATEL) method was used to analyze the causal hierarchical structure of eight core influencing factors. Next, a Fuzzy Cognitive Map (FCM) model was constructed to dynamically simulate the evolution of consumer cognition driven by key factors, with findings validated through in-depth interviews. Findings: The study identified the causal hierarchy of factors: intelligence (smart features), policy subsidies, charging speed, and driving range are fundamental "cause factors" that actively drive system changes; whereas vehicle price, comfort, and others are passive "effect factors." Among these, "vehicle price" serves as the central hub of the entire decision system, while "intelligence" is the strongest driving force. FCM simulations revealed that enhancing cause factors dynamically increases consumers' price sensitivity and environmental awareness. Additionally, highly educated and high-income groups currently dominate the market, and "driving range" remains the primary pain point for existing owners. Implications: This research offers a new dynamic analytical paradigm for understanding technology adoption behavior. It recommends that government policies shift from universal subsidies toward targeted support for core technology development and infrastructure construction. Enterprises should prioritize R&D investment in fundamental driving factors such as "intelligence.".

1. INTRODUCTION

Amid global efforts to combat climate change and ensure energy security, the green transportation revolution, led by new energy vehicles (NEVs), is transforming the automotive industry. Rapid economic and technological growth has driven a surge in vehicle ownership, making emissions from traditional fuel vehicles a major source of urban air pollution, threatening the environment and public health. NEVs, with higher energy efficiency, reduced reliance on petroleum, and low to zero operational emissions, offer a key solution to these challenges. As the world's largest automotive market, China has accelerated NEV development through strong policy support. According to the China Association of Automobile Manufacturers, cumulative NEV sales in China reached 12.866 million units in 2024, a 35.5% year-on-year increase, signaling strong industrial and market growth. Promoting NEVs is thus essential for reducing urban pollution, achieving "dual carbon" goals, safeguarding energy security, and enhancing industry competitiveness.

Despite the rapid expansion of the market, the widespread adoption of NEVs among consumers still faces a fundamental challenge: how to effectively increase market penetration. This challenge stems from the complexity of consumer purchase decisions. Numerous academic studies, both domestic and international, have examined the factors influencing NEV purchase intentions from multiple perspectives. These factors can generally be categorized into three levels.

First, technical and product attributes—such as driving range, charging convenience, safety and reliability, and intelligence level—which form the "hard" foundation of consumer decisions (Cheron & Zins, 1997; Higueras-Castillo et al., 2020; Wang et al., 2017; Xie et al., 2022; Li et al., 2021; Chen et al., 2019).

Second, policy and economic factors act as direct external drivers influencing purchase decisions. Research has shown that government economic subsidies, infrastructure development, and tax reductions all have significant positive effects on purchase intentions, with economic subsidies playing a particularly prominent role. However, these effects are context-dependent, being more pronounced among low-income groups or those with stronger environmental awareness (Ye et al., 2022; Cao et al., 2018; Wang, 2015; Sun & Xu, 2018; Hu et al., 2023; Chinen et al., 2022).

Third, consumer psychological and social factors serve as the "soft" internal motivators driving behavior. As environmental issues become increasingly severe, consumers' perceived green value, sense of environmental responsibility, and risk perception of air pollution consequences (i.e., psychological distance) have become important psychological variables affecting their purchase tendencies (Zu et al., 2019; Upadhyay & Kamble, 2023; Liu et al., 2021; Okada et al., 2019; Bi et al., 2023; Yang et al., 2020; Tunçel, 2022; Tu & Yang, 2019).

Although existing literature has identified key influencing factors, most studies rely on traditional statistical methods such as regression analysis or structural equation modeling (SEM), which are typically static and linear. While these approaches effectively determine which factors are important, they struggle to uncover the complex causal hierarchies, interaction intensities, and long-term dynamic feedback mechanisms among multiple factors. For example, is policy subsidy the fundamental cause driving the enhancement of consumers' environmental awareness, or merely a result interacting with other factors? How do improvements in intelligence levels dynamically affect consumers' sensitivity to price and driving range? These deeper systemic questions remain unanswered in current research. The limitations of these methods result in an incomplete understanding of the mechanisms underlying purchase intentions, thereby constraining the precision of policy-making and corporate marketing strategies.

To address this critical research gap, this study aims to move beyond traditional static factor analysis and uncover the dynamic interrelationship mechanisms influencing NEV purchase intentions. Focusing on residents of Zhengzhou, a representative new first-tier city in China, the study innovatively develops and applies an integrated model that combines the Decision-Making Trial and Evaluation Laboratory (DEMATEL) and Fuzzy Cognitive Map (FCM) methods. This methodological framework enables a two-stage, in-depth analysis: first, employing DEMATEL from a systems engineering perspective to calculate each factor's "influence degree," "affected degree," "centrality," and "causality," thereby clarifying the causal relationships among eight core factors—safety (*a1*), driving range (*a2*), charging speed (*a3*), comfort (*a4*), vehicle price (*a5*), policy subsidies (*a6*), intelligence (*a7*), and low-carbon environmental protection (*a8*)—and identifying which factors serve as fundamental drivers and which are resultant. Second, utilizing FCM, a dynamic simulation tool that integrates fuzzy logic and neural networks, to simulate and predict the dynamic feedback relationships among key factors, revealing the long-term evolutionary patterns of the entire consumer decision system.

Specifically, this study aims to address the following key questions: (1) What is the causal hierarchical structure among the key factors influencing the purchase intentions of NEVs among residents of Zhengzhou? (2) Within this complex system, which factors occupy central positions as fundamental drivers, and which are easily influenced as resultant factors? (3) How will changes in key driving factors dynamically influence consumers' core cognitions, such as price sensitivity and environmental awareness?

This study makes several significant contributions. Theoretically, it offers a novel, dynamic analytical framework for understanding technology adoption behavior. Practically, the findings provide scientific and forward-looking guidance for various stakeholders: assisting governments in formulating more precise and effective incentive policies centered on consumer needs; enabling enterprises to conduct targeted marketing based on user profiles and to focus R&D resources on technological bottlenecks that most concern consumers; and helping consumers develop a more rational understanding of the advantages and disadvantages of NEVs, thereby making purchase decisions better aligned with their individual needs. Ultimately, this study aims to promote the healthy and rapid development of the NEV market through an in-depth analysis of consumer behavior, contributing to improved air quality and the achievement of sustainable development goals.

2. LITERATURE REVIEW

Recent studies on NEV purchase intentions provide a foundation for understanding consumer decisions. This section reviews theories and key factors, highlighting research gaps and this study's contributions.

2.1 Theoretical Framework: Understanding Purchase Intention

Scholars use behavioral science theories to explain consumers' acceptance of NEVs and the underlying factors influencing purchase intentions.

The Theory of Planned Behavior (TPB) explains NEV purchase intentions through attitudes, subjective norms, and perceived control (Ackaah et al., 2021). Studies show government incentives shape attitudes and norms to boost intentions (Chatterjee et al., 2024), while altruistic personal norms strongly influence decisions alongside self-interest (Ji et al., 2024). Context matters: in Palestine, infrastructure limits reduce perceived control's effect (Ramadan & Othman, 2023), and emotions impact decisions differently across income groups (He et al., 2022), suggesting tailored marketing.

The Unified Theory of Acceptance and Use of Technology (UTAUT/TAM) highlights perceived usefulness and ease of use in user acceptance. Studies in Thailand and Malaysia show that performance and effort expectancy, social influence, attitude, and subjective norms positively affect purchase intentions, while perceived risk negatively impacts young technology adopters' decisions (Manutworakit & Choocharukul, 2022; Vafaei-Zadeh et al., 2022).

2.2 Core Influencing Factors: A Multidimensional Study

Under the guidance of the aforementioned theoretical framework, the influencing factors identified by specific empirical studies can be summarized into the following three dimensions.

Technology and product attributes are crucial for consumers. Initially, driving range, charging time, speed, and costs were top concerns (Cheron & Zins, 1997; Higueras-Castillo et al., 2020). Today, infrastructure readiness often outweighs single-range concerns (Wang et al., 2017). Innovative features impact purchase intention via perceived risk, moderated by lifestyle factors like fashion and environmental awareness (Xie et al., 2022). Product quality, performance, service, and comfort also boost purchase intention, while safety and facility risks remain key worries (Li et al., 2021; Chen et al., 2019).

The second factor involves policy and economic influences. Government policies, especially economic incentives (Ye et al., 2022; Cao et al., 2018), are key drivers of market development. Research shows that direct preferential policies like subsidies and tax reductions significantly boost purchase intention, with subsidies having a particularly strong effect (Wang, 2015). However, policy effectiveness varies by context. Sun and Xu (2018) found subsidies impact low-income groups, those with high policy awareness, and strong environmental consciousness more. As markets become more market-driven, Hu et al. (2023) observed in Chinese pilot cities that information and convenience policies (e.g., special license plates) now outweigh direct economic incentives, which have become insignificant. This aligns with Dong et al. (2020), who found cost factors no longer strongly influence car purchase intentions in some Chinese cities, with consumers prioritizing technological features instead. Additionally, Chinen et al. (2022) showed that downstream economic factors, such as price awareness and perceived benefits, positively affect consumers' willingness to buy recycled batteries.

Consumer psychology and social factors significantly influence decision-making. Environmental awareness—such as green perceived value (Zu et al., 2019), pro-environmental responsibility (Upadhyay & Kamble, 2023), and air pollution risk perception (Liu et al., 2021)—strongly drives purchase intention (Okada et al., 2019). Social and marketing factors also play key roles. Bi et al. (2023) show that green advertising boosts purchase intention by enhancing green perceived value and attitudes, especially among consumers focused on "impression management." Brand trust affects decisions through the pathway "trust → perceived benefits → attitude" (Yang et al., 2020). At the individual level, hedonic and social innovation motivations, like seeking personalization and expressing an eco-friendly identity, also increase purchase intention (Tunçel, 2022). Tu and Yang (2019) found that perceiving new energy electric vehicles as beneficial personally, environmentally, or nationally leads to more positive purchase attitudes.

2.3 Literature Review and Gaps

Existing studies highlight key factors across multiple dimensions but mainly use regression or SEM to analyze static correlations, neglecting complex causal interactions and dynamic feedback. This limits understanding of why factors like subsidies vary in effect or which factor drives systemic change.

This study addresses research gaps by introducing the DEMATEL-FCM model. It uses DEMATEL to clarify causal relationships and key factors from a systems engineering perspective, and employs the FCM to simulate and predict the dynamic evolution of consumer purchase intentions under various scenarios. This approach reveals the underlying mechanisms driving NEV purchase intentions more deeply and dynamically.

3 **METHODOLOGY**

3.1 Survey Design

3.1.1 Research Design and Objectives

This study examines consumer factors affecting NEV adoption in China using surveys and interviews, providing insights to support the NEV industry's growth.

3.1.2 Survey Instrument Development and Validation

The questionnaire was developed in three stages: literature review identified 11 factors; Python text mining captured public interest on NEVs; and interviews with 20 consumers refined the items. The questionnaire includes three sections: respondent basics, perceptions of NEVs, and factors influencing purchase intentions. A pilot study (N=107) confirmed the questionnaire's reliability (Cronbach's alpha = 0.894) and validity (KMO = 0.855; Bartlett's test $p < 0.001$), supporting factor analysis. Reliability and validity tests on 728 valid questionnaires confirmed the survey's stability, with internal consistency above 0.7 and a KMO of 0.927.

3.1.3 Sampling and Data Collection

This study surveyed residents of Zhengzhou City, chosen for its role as a major transportation hub in China, ensuring strong market representativeness. A four-stage stratified sampling scheme (Table 1) was used to enhance sample representativeness. The sample size was calculated with a 95% confidence level, 5% margin of error, and accounted for the multi-stage sampling design effect. Out of 910 distributed questionnaires, 728 valid responses were collected, yielding an effective response rate of about 80%.

Table 1 Sampling scheme

Stage	Sampling Unit	Sampling Method
First Stage	Five urban districts	Probability proportional to size sampling (PPS)
Second Stage	Streets	Simple random sampling
Third Stage	Communities	Simple random sampling
Fourth Stage	Residents	Quota sampling and convenience sampling

3.1.4 Quality Control and Data Processing

This study ensured data quality through comprehensive control at every stage. In the design phase, pre-surveys and in-depth interviews minimized questionnaire errors. During implementation, surveyors received systematic training, and logical validation in the online platform reduced errors and omissions. In data processing, rigorous validity, consistency, and logic checks were performed, with double-checking for coding and entry to minimize aggregation errors.

3.2 Data Analysis Models

3.2.1 DEMATEL Model

The DEMATEL, developed by the Battelle Association at the Geneva Research Center between 1972 and 1976, is a method for planning scientific and human affairs. Initially used to analyze complex global issues and conflicting phenomena (Mohammadde et al., 2019), DEMATEL employs matrix tools to reveal problem essences and formulate countermeasures. It transforms complex problems by comparing interrelationships among factors, calculating direct and indirect causal relationships and influence strengths through matrix operations. Using metrics like influence degree, influenced degree, cause degree, and centrality, DEMATEL visualizes causal relationships and influence levels via matrices and diagrams to support decision-making (Mavirk, 2018; Hotc et al., 2017).

We collected data, analyzed system elements, and established an indicator system. Key factors influencing consumer purchase intention—safety (*a1*), driving range (*a2*), charging speed (*a3*), comfort (*a4*), price (*a5*), policy subsidies (*a6*), intelligence (*a7*), and low-carbon protection (*a8*)—were identified via literature and expert input. The DEMATEL model steps are as follows:

Identify factors influencing consumer purchase intention, labeled a1 to a8.

Describe the influence of factor i (i = 1, 2, ..., 8) on factor j (j = 1, 2, ..., 8), denoted as x_{ij} :

$$x_{ij} = \begin{cases} 0 & \textit{No impact} \\ 1 & \textit{Some impact} \\ 2 & \textit{Moderate impact} \\ 3 & \textit{Strong impact} \end{cases} \quad (1)$$

Construct the direct influence matrix X:

$$X = \begin{bmatrix} x_{11} & \cdots & x_{18} \\ \vdots & \ddots & \vdots \\ x_{81} & \cdots & x_{88} \end{bmatrix} \quad (2)$$

Normalize matrix X by dividing each element by the maximum row sum to get matrix Q:

$$Q = X \Big/ \max_{1 \le i \le 8} \sum_{j=1}^{8} x_{ij} \quad (3)$$

Compute the impact matrix $R = Q\left(E - Q\right)^{-1}$, with E as the identity matrix.

Calculate the influence degree, influenced degree, centrality, and causality degree. The sum of each row in the comprehensive influence matrix R is the influence degree (G) of a factor, while the sum of each column is the influenced degree (F). Centrality (H) is the sum of influence and influenced degrees ($H = G + F$), and causality degree (M) is their difference ($M = G - F$).

Draw the causal relationship diagram, a two-dimensional graph with centrality on the horizontal axis and causality degree on the vertical axis. This diagram simplifies complex causal relationships into an easy-to-understand structure, guiding deeper problem analysis. It helps decision-makers formulate informed decisions based on causal or resultant factors among elements.

3.2.2 FCM Model

FCMs graphically represent problems, where nodes denote key factors in the decision-making environment, and connecting lines show relationships between them. FCMs merge fuzzy logic with neural networks, combining fuzzy rules with neural network learning algorithms. In an FCM, conceptual nodes represent entities, states, variables, and features within a system. These nodes, along with the directed edges connecting them, embed rich knowledge and express fuzzy reasoning through their relationships. FCMs are widely used to simulate practical problems such as modeling complex systems, market optimization, and artificial emotion prediction. FCMs function as effective reasoning engines, enabling qualitative and quantitative simulation of complex fuzzy systems. Let the concept nodes in an FCM be denoted as A_n, where the system comprises n factors, each represented by state values. These nodes exhibit varying states and values across iterations. Relationships between nodes are indicated by directed arcs, pointing toward the influenced node. Each arc carries a weight (W_{ij}) that quantifies the influence between nodes. The state of node A_n is represented by S_i.

(1) If $W_{ij} > 0$, a positive causal relationship exists between nodes A_i and A_j. An increase in node A_i's state value S_i causes an increase in node A_j's state value S_j; similarly, a decrease in S_i causes a decrease in S_j.

(2) If $W_{ij} < 0$, a negative causal relationship exists between nodes A_i and A_j. An increase in A_i's state value S_i causes a decrease in A_j's state value S_j, while a decrease in S_i causes an increase in S_j.

(3) If $W_{ij} = 0$, nodes A_i and A_j are not causally linked. Figure 1 shows a FCM with nodes A_1 to A_4; W_{14} represents the effect of A_1 on A_4, where a unit change in A_1 alters A_4 by W_{14} units.

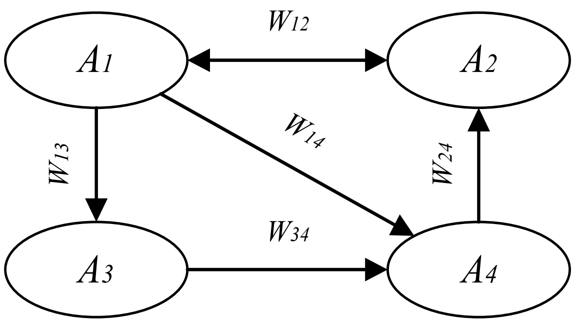

Figure 1 FCM structure diagram

Developing a FCM involves three key steps:

Identify and standardize concept nodes affecting NEV purchases using equation (4).

$$x^* = \frac{x_i - \min x}{\max x - \min x} \qquad (4)$$

Identify relationships between conceptual nodes and clarify causal links among factors using DEMATEL theory. The relationships between concept nodes are described as "zero," "weak positive," "moderate positive," and "strong positive," with corresponding quantitative values of 0, 1, 2, and 3, respectively. After quantification, the overall evaluation result within the domain is determined, as shown in equation (5).

$$\omega_{ij} = \frac{\sum_{k=1}^{N} b_k W_k}{N} \quad (5)$$

where, N is the number of experts, b_k the credibility of the k-th consumer (usually 1), and W_k the weight they assign to concept node relationships.

Assess the strength of relationships between conceptual nodes. Experts (representative consumers) provide fuzzy semantic variables indicating influence levels, which are converted from qualitative to quantitative values using established rules to assign numerical values to all evaluation objects. After constructing the complete FCM, simulate the system. The reasoning mechanism is as follows:

$$S_j^t = f(k_1^i \sum_{i=1, i\neq j}^{n} S_i^{t-1} W_{ij} + k_2^i S_j^{t-1}) \qquad (6)$$

where, S_j^t is the j-th node's state at time t, S_i^{t-1} the i-th node's state at t-1, and W_{ij} the influence weight from node i to j. Kosko (1986) noted that if a node's past value is excluded from its update, then $k_2^i = 0$ and $k_1^i = 1$. The threshold function f is usually the unipolar S-shaped function :

$$f(x) = \frac{1}{1+e^{-x}} \quad (7)$$

According to FCM reasoning, when the model's initial input changes, the dynamic system uses the influence matrix to generate the next output state, iterating until it reaches a fixed point, limit cycle, or chaotic state. Analyzing the system's state after each iteration reveals its dynamic characteristics and evolution.

3. RESULTS

4.1 Sample Demographics and Purchase Intentions

The planned sample size for this survey was 910 people, with 728 valid responses collected, resulting in an effective response rate of 80%. We analyzed the sample composition and purchase intentions based on gender, age, education level, monthly income, and current car ownership status.

The gender ratio of respondents was balanced, with females at 48.9% and males at 51.1%, minimizing gender bias and enhancing the study's validity. Age distribution showed 66.21% aged 20-29, 15.11% aged 40-49, 11.81% aged 30-39, 4.95% over 50, and 1.92% under 19.

Most respondents hold a bachelor's degree (56.87%, IV), followed by master's or higher (27.75%, V) and associate degrees (10.44%, III). Fewer have a high school diploma (2.75%, II) or less (2.2%, I). This diverse sample confirms the survey’s thoroughness and randomness.

Data show that NEVs cost 20% to 30% more than comparable fuel-powered cars. We hypothesized that economic strength significantly affects respondents’ willingness to purchase. We assessed economic strength by monthly income, finding a balanced distribution: 32.69% earned less than 3,000 yuan (VI); about 23% earned 3,001–6,000 yuan (VII) and 6,001–9,000 yuan each (VIII); and approximately 10% earned 9,001–12,000 yuan (IX) and above 12,000 yuan each (X). Among respondents, 37.36% owned vehicles, mostly fuel-powered (83.09%), while 62.64% did not. Among non-owners, 40.79% preferred hybrids, 12.28% pure electric, and 28.95% fuel-powered cars. Meanwhile, 16.67% had no plans to buy a vehicle.

Through chi-square test analysis, both respondents' education levels and monthly incomes are significantly correlated with their types of purchase intention ($p < 0.001$). Specifically, respondents with higher education levels have a greater proportion of purchasing NEVs (including those who have already purchased and those intending to purchase). Similarly, respondents with higher monthly incomes also demonstrate a stronger tendency to purchase NEVs (see Appendix Tables A-1 and A-2).

4.2 Consumer Awareness and Satisfaction

For current vehicle owners, the survey examined their satisfaction with various aspects of their vehicles. The results indicated that "comfort" and "after-sales service" were the two dimensions with the highest satisfaction levels. Conversely, "driving range" was the primary source of dissatisfaction, with 8.7% of owners reporting they were "very dissatisfied" with it. Regarding policy awareness, respondents’ understanding of NEV-related policies was generally moderate, with an average score of 5.426 out of 13. Analysis of variance revealed a significant difference in policy awareness based on purchase intention types ($F = 3.966$, $p = 0.000$), showing that consumers with greater policy knowledge were more inclined to choose NEVs. Principal component analysis identified the top two policy measures most influential on purchase intention as "appropriate reduction or exemption of purchase tax" (weight 21.21%) and "providing certain price subsidies" (weight 20.93%), as presented in Table 2.

Table 2 Linear combination coefficients and weight results

Name	**Principal Component 1**	**Composite Score Coefficient**	**Weight**
Characteristic root	3.798		
Variance explained	75.95%		
Purchase tax	0.4736	0.4736	21.21%
Subsidy	0.4674	0.4674	20.93%
Vehicle registration	0.4576	0.4576	20.50%
Right of way	0.4237	0.4237	18.98%
Supporting facilities	0.4102	0.4102	18.38%

4.3 Causal Hierarchical Structure of Influencing Factors: Results of DEMATEL Analysis

To investigate the causal relationships among the eight core influencing factors (*a1–a8*), this study employed the DEMATEL model. The calculated values for each factor's influence degree, influenced degree, centrality, and causality are presented in Table 3. Using centrality as the horizontal axis and causality as the vertical axis, the cause-effect diagram is shown in Figure 2.

Table 3 DEMATEL calculation results

Factors	**Influence degree**	**Influenced degree**	**centrality**	**causality**
a1	1.483	1.705	3.188	-0.222
a2	1.819	1.790	3.609	0.029
a3	1.969	1.896	3.864	0.073
a4	1.321	2.033	3.355	-0.712
a5	2.823	2.933	5.756	-0.110
a6	1.811	1.115	2.926	0.697
a7	2.710	2.028	4.738	0.682
a8	1.225	1.661	2.886	-0.436

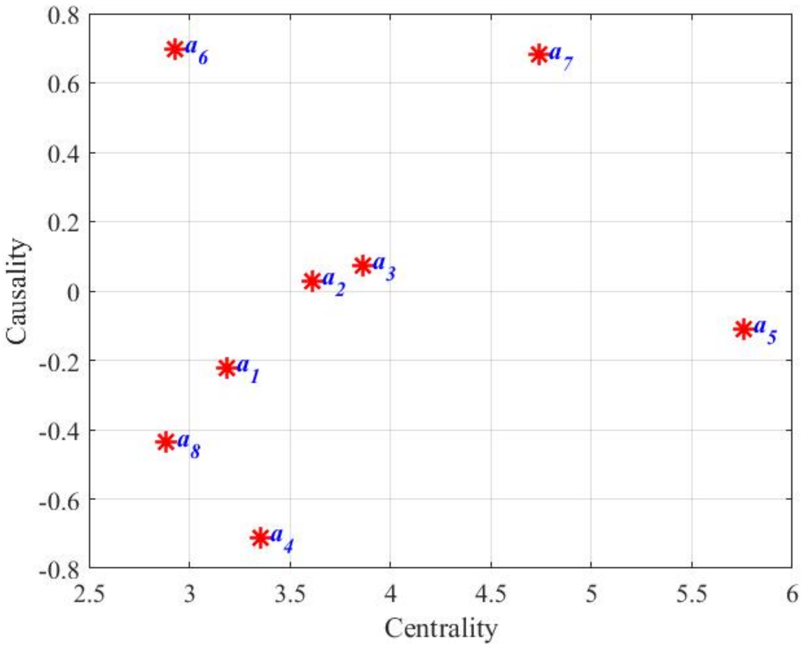

Figure 2 Cause-effect diagram

The causal relationship diagram based on centrality (horizontal axis) and causality (vertical axis) is shown in Figure 2. According to whether the causality is greater than zero, the eight factors can be divided into cause factors and effect factors.

Cause factors (causality > 0) include policy subsidies (*a6*), intelligence (*a7*), charging speed (*a3*), and driving range (*a2*).

Effect factors (causality < 0) include comfort (*a4*), low carbon and environmental protection (*a8*), safety (*a1*), and car price (*a5*).

Based on the centrality values, the importance ranking of the factors in the entire system is: car price > intelligence > charging speed > driving range > comfort > safety > policy subsidies > low carbon and environmental protection.

4.4 Dynamic Correlation of Influencing Factors: FCM Simulation Results

4.4.1 Concept Node Identification

As can be seen from the above, the causal degrees and centrality of driving range, charging speed, policy subsidies, and intelligence are all greater than zero. However, since the centrality of driving range and charging speed are similar, and the centrality of charging speed is greater than that of driving range, charging speed, policy subsidies, and intelligence are selected as the causal variables for the dynamic correlation study of factors. Additionally, because the causal degree is less than zero and centrality is greater than zero, safety, comfort, vehicle price, and low-carbon environmental protection are identified as outcome variables.

The initial values of the FCM concept nodes were obtained from literature reference 33 (Yang et al., 2018) and standardized using formula (4), as shown in Table 4.

Table 4 Initial values of factors affecting NEV purchase intent

Factors	a_1	a_2	a_3	a_4	a_5	a_6	a_7	a_8
Initial Value	0.56	0.161	0.63	0.625	0.77	0.3	0.2	0.0952

4.4.2 Concept Node Relationships

The dynamic correlation model of factors influencing the willingness to purchase NEVs is shown in Figure 3.

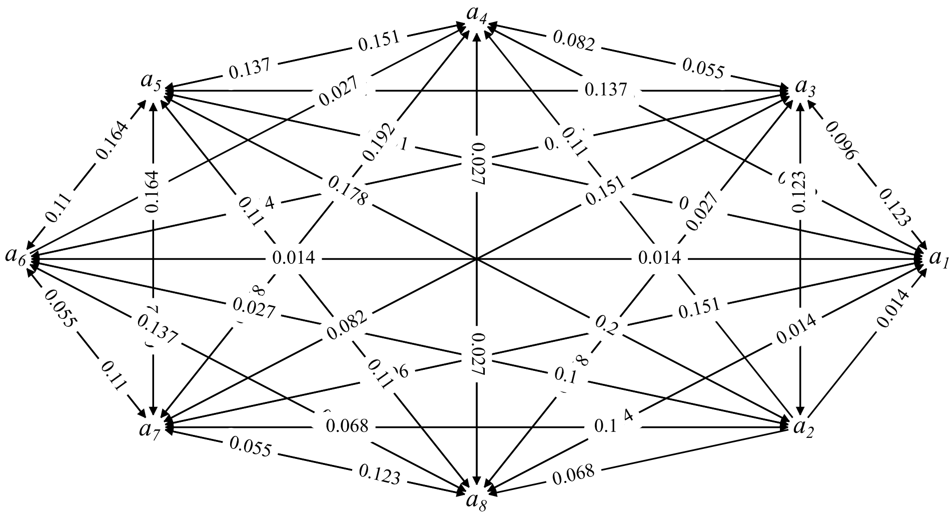

Figure 3 Model of factors influencing NEV purchase intentions

In Figure 3, if a line has two weight values, each follows a clockwise convention: the first weight represents the influence from the factor with the smaller index to the factor with the larger index, while the second weight represents the influence from the factor with the larger index to the factor with the smaller index.

DEMATEL analysis shows automobile price as the key factor influencing NEV purchase decisions. Other causal variables may also affect consumer sensitivity to NEV prices. A simulation of the dynamic correlation model was conducted to explore these interactions.

Starting from a baseline with unchanged factor values, the effect of causal variables on automobile price trends is assessed. When prices rise, causal variables that speed up changes increase short-term consumer sensitivity to NEV prices; if they slow changes, sensitivity decreases. The opposite applies when prices fall. By varying causal variables incrementally across 11 × 11 × 11 scenarios, their impact on the steady state reveals whether they influence long-term consumer sensitivity to NEV prices.

4.4.3 Simulation analysis

1. Dynamic Effects on Price Sensitivity

Scenario 1: Baseline Scenario. This scenario simulates changes in NEV prices under the current system conditions.

The following scenarios simulate adjustments to the influencing factors within the causal variables to observe changes in the outcome variables.

Scenario 2: Charging Speed Driven. One causal variable is selected; here, the charging speed status value is set to 1, while the other factors remain unchanged.

Scenario 3: Policy Subsidy Driven. The policy subsidy status is set to 1 here, while all other factors remain unchanged.

Scenario 4: Intelligence-Driven. The intelligence status value is set to 1 here, while other factors remain unchanged.

Simulations for the four scenarios described above were conducted, and the trend of NEV prices is illustrated in Figure 4.

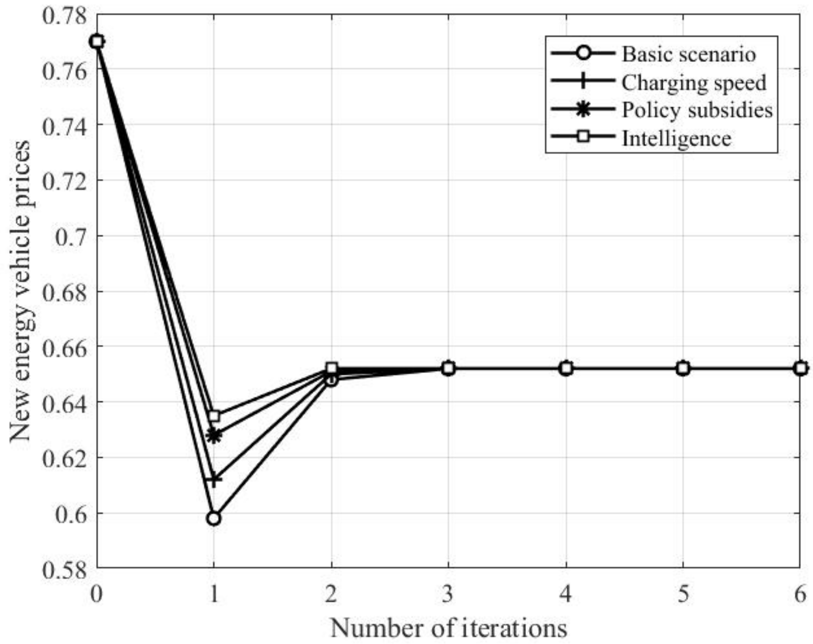

Figure 4 NEV price trends

Figure 4 shows that as NEVs become widespread, consumer price sensitivity decreases. However, charging speed, policy subsidies, and intelligence temporarily increase sensitivity, ranked from greatest to least: intelligence, policy subsidies, then charging speed. Advanced intelligent features notably raise price sensitivity.

Charging speed, policy subsidies, and intelligence were varied from 0 to 1 in 0.1 increments, generating 11 × 11 × 11 scenarios. Figure 5 shows the resulting steady-state NEV price simulation.

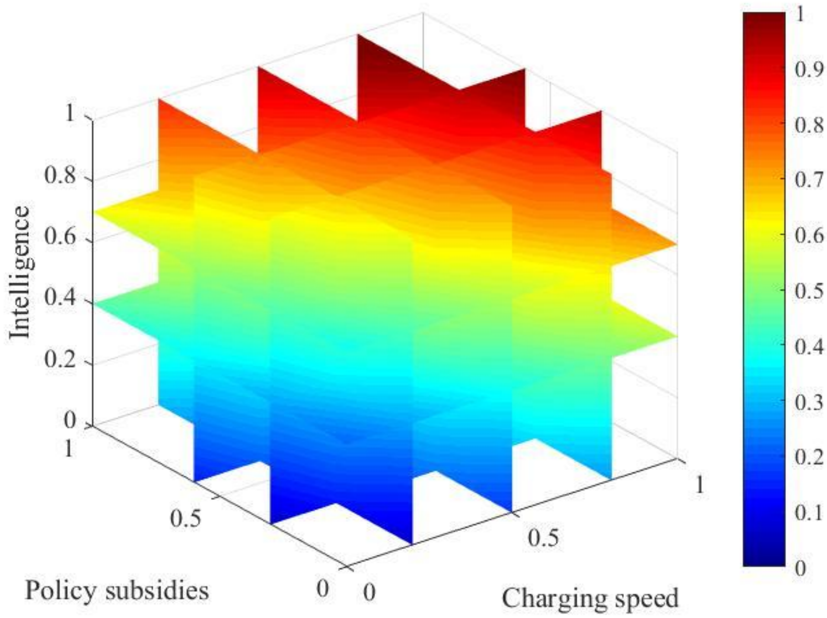

Figure 5 Steady-state simulation of NEV prices

Figure 5 shows that all three causal variables positively affect the steady-state price of NEVs, indicating their long-term influence on consumers' price sensitivity. When the policy subsidy is 0.5, increasing charging speed from 0 to 1 heightens consumers' price sensitivity. This suggests that faster charging speeds amplify consumers' responsiveness to price. Similarly, when charging speed is 1, increasing intelligence from 0 to 1 also raises price sensitivity.

2. Dynamic Impact on Environmental Awareness

Model stability was verified through trend and steady-state simulations of the low-carbon environmental protection variable, shown in Figures 6 and 7.

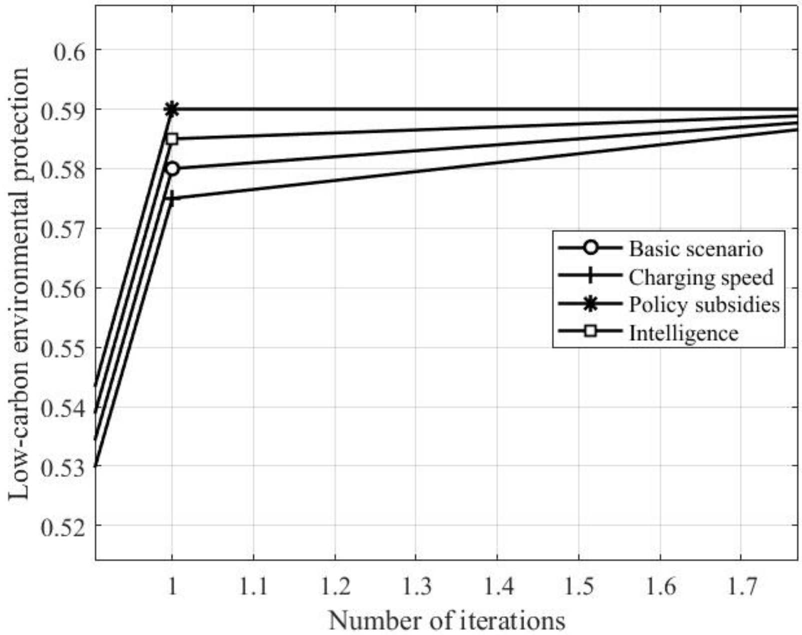

Figure 6 Low-Carbon environmental protection trends

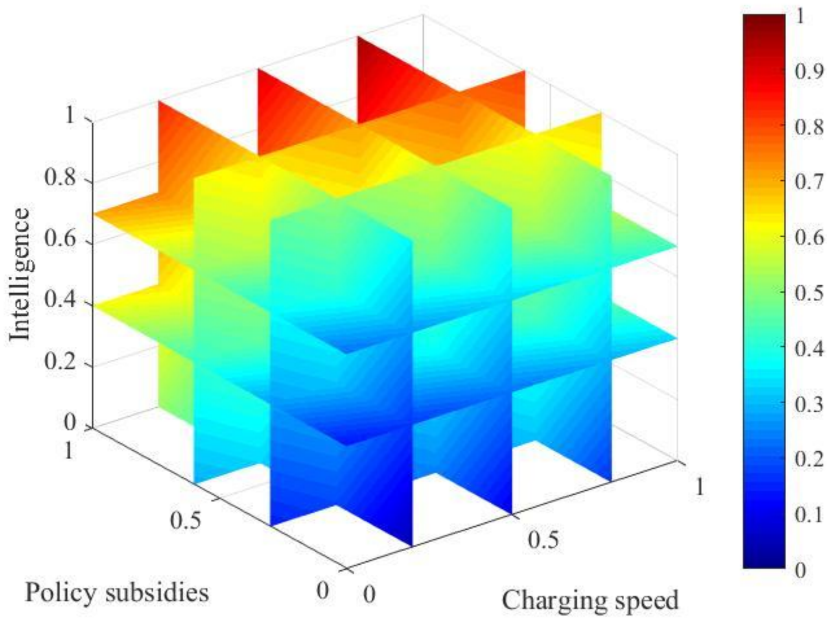

Figure 7 Steady-state simulation of Low-Carbon environmental protection

Figures 6 and 7 show that consumers are increasingly aware of low-carbon, eco-friendly practices. The factors influencing this awareness, ranked from most to least impactful, are policy subsidies, intelligence (smart features), and charging speed. Government subsidies, improved vehicle intelligence, and faster charging all enhance consumers' environmental awareness. The simulated scenarios reflect real-world conditions, demonstrating the model's stability and the reliability of its conclusions.

4. DISCUSSION

5.1 The Causal Structure and Central Hub of the Consumer Decision System

One of the most critical findings of this study is that the system of factors influencing consumers' purchase intentions, as revealed by the DEMATEL model, is not a flat structure but exhibits a clear causal hierarchy. By analyzing each factor's centrality (system importance) and causality (causal attribute), we can position them within a four-quadrant analytical framework for deeper exploration, thereby uncovering the system's intrinsic operational logic.

Strong Driving Factors (High Centrality, High Causality): Identified as the sole “strong driving factor” in this study, “Intelligent Features (*a7*)” holds a particularly prominent position. Its causality score (0.682) and centrality score (4.738) are both high, indicating that it is not only the fundamental cause driving system changes but also occupies a central role within the entire decision system, serving as the “core driving force.”

Driving Factors (Low Centrality, High Causality): “Policy Subsidies (*a6*),” “Charging Speed (*a3*),” and “Driving Range (*a2*)” are the primary driving forces within the system. These factors share the characteristic of having a positive causality score but relatively low centrality, identifying them as key “initial variables” that initiate the consumer decision-making process.

Dependent Factors (High Centrality, Low Causality): “Car Price (*a5*)” is a typical dependent factor. Its causality score is negative (-0.110), but its centrality is the highest among all factors (5.756), indicating that although it is passively influenced, it serves as the system's core hub where all causal chains ultimately converge.

Characteristic Factors with low centrality and low causality—namely “Comfort (*a4*),” “Low Carbon and Environmental Protection (*a8*),” and “Safety (*a1*)”—indicate relatively independent “final perceptions” or “outcome characteristics” formed by consumers after comprehensive evaluation.

This finding deepens our understanding of the consumer decision-making process. Traditional views often regard “car price” as the primary decision factor; however, this study finds that while it is the core hub, it is essentially a “dependent factor.” Consumers' price perceptions do not exist in isolation but are jointly shaped by a series of upstream factors such as the level of intelligent features, driving range, and policy incentives. One potential buyer interviewed mentioned, “Although I really like those smart features, in the end, it comes down to whether the extra cost for these features is worth it,” vividly confirming the transmission effect of upstream causal factors like “intelligent features” on the core outcome factor of “price.”

5.2 "Intelligentization": The Shift from a "Bonus Feature" to a "Core Driving Force"

As the only "strong driving factor" identified in this study, the status of "intelligentization" is particularly prominent. Its combination of high causality and high centrality makes it not only the system's "strongest driving force but also signifies a fundamental shift in consumers' perception of NEVs. Cars are evolving from traditional transportation tools into "intelligent mobile terminals" integrated with advanced technology. In interviews, a current car owner repeatedly emphasized that what attracted him to purchase was not just the electric driving performance but also the technological experiences, such as "automatic parking and intelligent voice interaction, that conventional fuel vehicles cannot match. This finding echoes the conclusion of Xie et al. (2022) that product "innovative features" drive purchase intention by influencing perceived risk and further clarifies that "intelligentization" is the core embodiment of innovative features at the current stage.

5.3 The Dual Effects of “Policy Subsidies”: Economic Leverage and Awareness Catalyst

As a key driving factor, the FCM simulation results for “policy subsidies” reveal significant dual effects. On one hand, subsidies act as an economic lever, dynamically increasing consumers' price sensitivity by shaping their cost expectations. On the other hand, they serve as a catalyst for environmental awareness, representing the strongest driver in enhancing consumers' low-carbon and eco-friendly consciousness. This indicates that subsidies are not merely financial incentives but also powerful social signals that communicate the government's advocacy and endorsement of green travel to consumers, thereby activating their personal norms and sense of environmental responsibility. This provides a practical explanation for the study by Ji et al. (2024), which found that “personal norms” are the strongest drivers of purchase intention—namely, that policy can serve as an effective external mechanism to activate personal norms.

5.4 The Paradox of "Driving Range": The Misalignment Between Decision Weights and Experience Pain Points

As another important "driving factor," the role misalignment of "driving range" in decision-making and user experience is worth deep reflection. In the DEMATEL importance ranking, driving range (centrality 3.609) is significant but ranks below price, intelligence features, and charging speed. However, in satisfaction surveys of current car owners, it emerges as the primary pain point in actual use. Interviews also confirm this: potential buyers may tolerate a discount on the nominal driving range, but real owners are deeply troubled by "energy replenishment anxiety" and "uncertainty of actual range." This phenomenon of being "optimistic before purchase, pessimistic after experience" reveals the current market information asymmetry and highlights the necessity of considering driving range and the convenience of charging infrastructure (perceived behavioral control) as an integrated whole.

5. CONCLUSION

6.1 Research Conclusions

This study conducted a mixed-methods survey of residents in Zhengzhou City to systematically analyze the dynamic interrelated mechanisms influencing the willingness to purchase NEVs, yielding the following key conclusions:

1. Market Trends and Consumer Profiles: The NEV market is currently in an accelerated penetration phase, with highly educated and high-income groups serving as the main driving force and early adopters.

2. Causal Hierarchical Structure: Consumer decision-making is a complex system involving multiple interacting factors. Intelligence (smart features), policy subsidies, charging speed, and driving range are fundamental "cause factors" at the upstream level; whereas vehicle price, comfort, safety, and environmental friendliness are "result factors" at the downstream level.

3. Identification of Core Factors: The study clarified the roles of various factors within the system. "Vehicle price," as a typical "dependent factor," acts as the central hub of the entire decision-making system; while "intelligence" (smart features), as a "strong driving factor," serves as the most powerful driving force behind system evolution.

4. Dynamic Interrelated Mechanisms: Enhancing cause factors such as the level of intelligence, the strength of policy subsidies, and charging speed dynamically increases consumers' price sensitivity and environmental awareness.

5. Core Usage Pain Points: "Driving range" is currently the primary pain point for vehicle owners, revealing a misalignment between decision-making weight and actual user experience pain points.

6.2 Practical Implications

For the government, policies should transition from providing universal subsidies to offering targeted structural support. This approach involves continuing to reduce consumer barriers through fiscal and tax measures while simultaneously allocating increased resources to facilitate advancements in core technologies, including intelligent features and charging speed, as well as enhancing charging infrastructure.

For enterprises, research and development resources should be strategically allocated to prioritize and other significant driving factors to effectively stimulate market demand. Concurrently, companies must recognize and address practical challenges associated with by implementing transparent range testing standards, thereby fostering consumers' long-term trust.

For consumers, it is essential that the driving range of a vehicle aligns precisely with their primary usage scenarios to prevent inconvenience resulting from overly optimistic expectations at the time of purchase.

6.3 Limitations and Future Directions

The innovation of this study lies in the application of the integrated DEMATEL-FCM model, which reveals the formation mechanism of purchase intention from a dynamic and systemic perspective. However, the research sample was limited to Zhengzhou City, so the generalizability of the conclusions remains to be verified. Additionally, the cross-sectional design did not capture long-term changes in consumer attitudes. Future research could conduct multi-city comparisons or adopt longitudinal study designs to better understand the evolution of consumer attitudes amid ongoing market and technological developments..

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