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USED CAR MARKETING STRATEGY RECOMMENDATION: A STRUCTURAL EQUATION MODELING APPROACH

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Abstract. In recent years, China's used car market has experienced rapid growth. However, constrained by non-standardization, lack of trustworthiness, and dual competitive pressures from emerging e-commerce platforms and traditional dealers, optimizing corporate marketing strategies has become an urgent priority. This study takes three first-tier city used car enterprises—Beijing Guazi, Guangzhou Cheyou, and Shanghai Youxin, as research subjects, employing quantitative research methods to explore the influencing factors behind performance improvement in the used car industry. The results show that: (1) the marketing mix (4Ps) serves as the core driver of customer satisfaction, attractiveness, and corporate performance, directly determining the effectiveness of personalized marketing implementation; (2) while personalized marketing requires precise execution, external environmental factors exert limited influence; (3) enhancing corporate performance necessitates the synergy of both marketing and non-marketing factors. Based on these findings, it is recommended that enterprises center their efforts on the 4Ps to optimize product pricing, channel integration, and other aspects, deepen big data-driven precision personalized marketing, and establish a full-link mechanism of "acquiring customers through marketing—retaining customers with quality—locking in customers via service." This study provides empirical support for strategy optimization in used car enterprises and enriches both the theory and practice of marketing transformation in the industry.

Keywords: China; used cars; improve performance; marketing mix; personalization; quantitative research

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1. Introduction

In 2024, China saw about 19 million used car sales, nearly a fivefold increase since 2010, reflecting strong market growth (China Automobile Dealers Association, 2025). The expansion of China's used car market size and growth in transaction volume also reflect rising consumer acceptance of second-hand goods and improved market circulation efficiency. In the current used car market environment, used car sales enterprises face intense competition from emerging e-commerce platforms and traditional dealers (Feng, Qin & Zhi, 2025). These challenges impede their performance improvement and call for optimized marketing strategies to address. The

pattern where intensified market competition constrains enterprise performance growth is prevalent across transitional industries, and optimizing marketing strategies represents a core pathway for enterprises to break through competitive barriers and achieve differentiated development.

This study focuses on three leading used car enterprises in first-tier cities—Beijing Guazi, Guangzhou Cheyou, and Shanghai Youxin. Through cross-regional comparative analysis, it accurately captures the impact of market heterogeneity on corporate strategies, providing empirical support for the industry's differentiated development and helping enterprises optimize strategies and enhance performance.

At the theoretical level, this research fills the gap in studies on marketing strategies at the enterprise level in China's used car industry, enriching academic literature on corporate competitive strategies amid automotive industry transformation. At the practical level, the findings will offer actionable strategic references for enterprises, directly improving consumer purchasing experiences.

2. Review Literature and Hypotheses

Among the multi-dimensional research literatures focusing on the global and Chinese used car markets, the following key findings are as follows.

In China, policy measures (such as removal of relocation restrictions and tax cuts) and upgraded consumer concepts (emphasizing environmental protection and cost-effectiveness) serve as core drivers (Barwick, Cao & Li, 2021). China's transaction volume is expected to exceed 30 million units by 2025, with regional strategies diverging: First-tier cities are dominated by brand services (e.g., certified warranties, transparent vehicle conditions); second- and third-tier cities exhibit high price sensitivity, requiring channel penetration (Liu & Song, 2023; Zhang et al., 2025).

Digital marketing, social media, and integration have become trends (Nithisathian et al., 2020). Younger groups (aged 25–35) exhibit high online platform usage, yet enterprises often lack word-of-mouth incentives (Azadnia et al., 2022; Siregar, Suroso & Krisnatuti, 2024). Key decision factors are price, vehicle condition transparency, and after-sales guarantees. The trust-cost dilemma has emerged: vehicle condition transparency (via blockchain) and third-party inspections enhance trust, but cost control remains unresolved; dynamic pricing improves short-term efficiency, yet long-term brand premium quantification is difficult (Engelmann et al., 2022; Beck, Wuyts & Jap, 2023; Engelmann & Schwabe, 2024; Sun et al., 2025).

Traditional dealers compete against online platforms, where service and brand determine success (Feng, Qin & Zhi, 2025). Current used car sales companies (e.g., Beijing Guazi, Guangzhou Cheyou, Shanghai Youxin, etc.) face multiple challenges. Emerging e-commerce platforms have rapidly captured market share through strategies like low-price models, large-scale advertising, and big data-driven precision marketing (Steinberg, 2021). Traditional dealers have also intensified competition by leveraging the advantages of their offline after-sales networks, making market share capture increasingly difficult (Feng, Qin & Zhi, 2025).

Consumer demands are becoming increasingly diverse, and there is pressure from imports, as well as a preference for new cars (Ramani, 2025). Yet enterprises lag in demand response speed and personalized service adaptation. Coupled with issues such as insufficient transparency in vehicle condition, building trust remains a significant challenge. Internal operational shortcomings are equally prominent: Inefficient integration of digital marketing tools (social media, SEO) leads to low lead conversion rates; Business is overly concentrated on the transaction process, with follow-up services (e.g., after-sales maintenance) lagging behind (Feng, Qin & Zhi, 2025); Profit models rely heavily on purchase-resale spreads, causing profit margins to narrow continuously amid intensifying competition; High costs for brand building and technology R&D create an urgent need to control expenses and improve efficiency (Azadnia et al., 2022).

Theoretical framework of the study is based on the following theories. Marketing Mix Theory (4Ps) framework can be used in the car market, validating its effectiveness in enhancing market competitiveness through dynamic pricing and optimization of the online-to-offline (O2O) distribution system.

Personalized Marketing Theory can be applied for car industry. Chen, Zhang and Wang (2025) provided empirical support for used car enterprises to design differentiated communication strategies and improve customer satisfaction by leveraging precision recommendation technology based on big data analysis.

Relationship Marketing Theory emphasizes role of relationship marketing guiding used car enterprises to build long-term customer relationships through loyalty programs and emotional connections. Customer Value Theory proposes a performance measurement framework encompassing four dimensions of customer value (functional, emotional, social, and cost), which helps used car enterprises optimize perceived customer value (Azadnia et al., 2022). Service Marketing Theory suggests the service marketing 7Ps model, which could be applied to analyze companies' experience in used car sales, verifying its role in enhancing the full-process pre-sale, in-sale, and post-sale services. The theoretical framework diagram is shown in Figure 1.

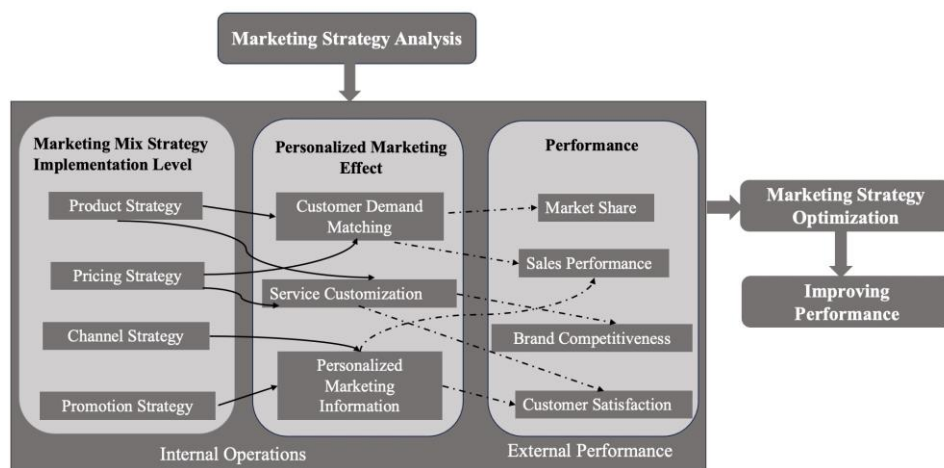


Figure 1. Theoretical framework for research on used car company marketing strategy

Source: the authors

Statistical analysis was used to validate research hypotheses. The following preliminary hypotheses are proposed:

H1. Respondents are satisfied with the current product, pricing, distribution, and promotion strategies of Chinese used car companies.

H2. The marketing mix strategies (product, pricing, distribution, promotion) of Chinese used car companies effectively meet customer needs to a certain extent.

H3. Chinese used car companies demonstrate a certain degree of effectiveness in implementing personalized marketing strategies (content marketing, social media interaction, promotions, customer service).

H4. The implementation level of marketing mix strategies has a significant positive impact on the effectiveness of personalized marketing strategies in Chinese used car companies.

H5. Chinese used car companies face a series of major challenges and obstacles (including product development bottlenecks, pricing strategy dilemmas, distribution channel barriers, and promotion method limitations) when implementing their marketing mix strategies.

H6. Based on the research findings, propose marketing strategy recommendation methods to improve corporate performance.

Focusing on the core topic of "optimizing marketing strategies and enhancing performance for Chinese used car enterprises," this study systematically constructs a logical analytical framework of "marketing strategy implementation → customer indicators (satisfaction, attractiveness) → business performance," grounded in the

Resource-Based View (RBV), Relationship Marketing Theory, and Dynamic Capabilities Theory. The specific variable design is as follows:

Independent variables: Marketing mix strategy, effectiveness of personalized marketing, personalized marketing strategy, market competition pressure, and changes in consumer demand.

Dependent variables: Customer satisfaction, customer attractiveness, marketing mix strategy, effectiveness of personalized marketing strategy, personalized marketing strategy, and business performance.

Moderating variables: The effectiveness of personalized marketing strategies in attracting customers and internal resources.

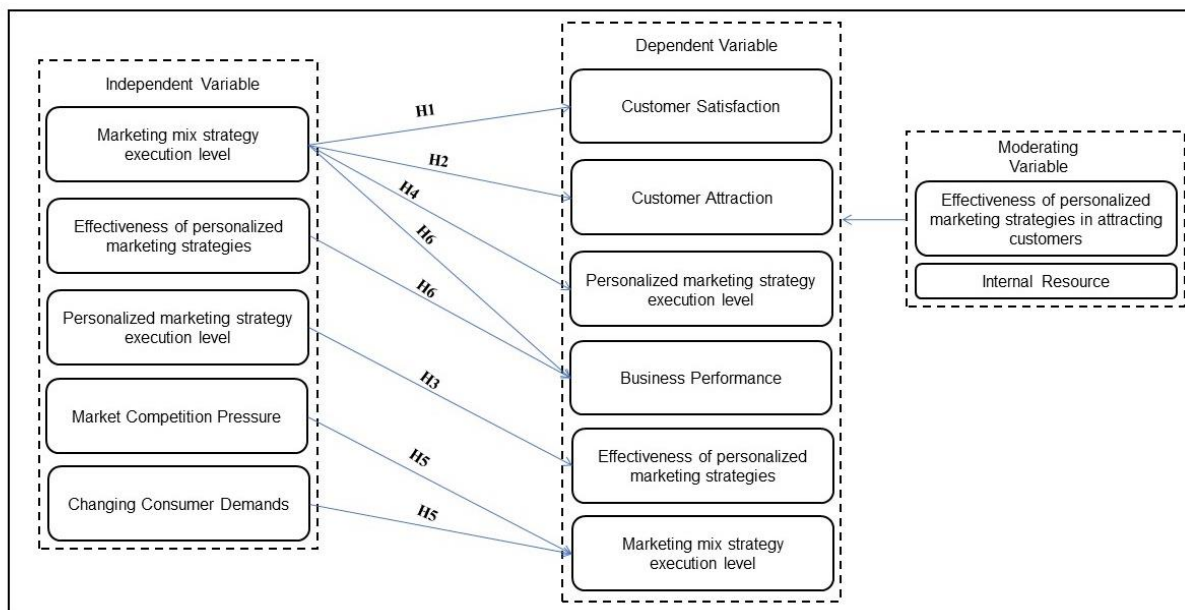


Figure 2. Conceptual Framework of Used Car Company Marketing Strategy Recommendation Research

Source: the authors

The relationships among these variables are illustrated in Figure 2, ultimately demonstrating the logical path through which marketing strategy implementation influences business performance via customer indicators.

3. Research Methods

3.1. Research Design

The study focuses on optimizing marketing strategies for used car businesses, adopting quantitative analysis methods to collect data through questionnaire surveys. It aims to identify key factors influencing strategies and test hypotheses, providing data-driven recommendations for enterprises. The sample covers three companies—Beijing Guazi, Guangzhou Cheyou, and Shanghai Youxin—with a total of 360 respondents (including managers, employees, and customers). Random sampling was conducted proportionally by organizational hierarchy to ensure representativeness. Descriptive statistics, correlation analysis, and other methods were employed to evaluate the impact of factors and test the hypotheses. Adhering to ethical standards, the study ensures participant anonymity and data security, with operations regulated through informed consent procedures. It offers multi-dimensional insights into the current status of used car marketing strategies and pathways for optimization.

3.2. Instrumentation

This study uses questionnaires as the primary tool, aiming to analyze the recommended paths of used car marketing strategies and their impact on performance. The questionnaire is designed based on the research

objectives, covering dimensions such as product, pricing, channel, promotion, personalized marketing, and customer value. The data is comprehensive, encompassing key factors for marketing strategies.

The questionnaire consists of two parts, and the questions are multiple-choice questions.

1. Part I: Basic information of respondents

Mainly collect the basic information of the respondents, including job category (senior, middle-level, front-line employees, users), age, gender, education and years of work experience.

2. Part II: Evaluation of existing marketing strategies (50 questions), see Table 1.

Table 1. Variables, items, survey questions and source reference

Variables	Items	Survey Questions	Source/Reference
Effectiveness of personalized marketing strategies in attracting customers (Items 1)	EPMS1	Personalized marketing messages make me more likely to consider buying a used car.	Chen, Zhang & Wang, 2025
	EPMS2	I believe that personalised promotions align with my specific needs and preferences.	
	EPMS3	Personalized recommendations increase my trust in the company.	
	EPMS4	I am more engaged with marketing messages that are tailored to me.	
	EPMS5	Personalized marketing encourages me to revisit the seller/platform.	
Internal Resource (Items 2)	IR2	The company has sufficient human resources with marketing expertise.	He et al., 2024
	IR3	Technological resources are effectively used to implement strategies.	
	IR4	Organizational structure supports the execution of marketing plans.	
	IR5	Internal knowledge and capabilities contribute to successful marketing.	
	IR2	The company has sufficient human resources with marketing expertise.	
Customer Satisfaction (Items 3)	CS1	I am satisfied with the overall purchasing experience.	Azadnia et al., 2022
	CS2	The company provides reliable and trustworthy services.	
	CS3	My expectations of the product/service are consistently met.	
	CS4	I would recommend this company to others.	
	CS5	I intend to repurchase from this company in the future.	
Customer Attraction (Items 4)	CA1	The company's marketing efforts attract my attention effectively.	Lee, Kim & Kim, 2021
	CA2	I am attracted to exploring the company's offerings after seeing its marketing.	
	CA3	Marketing campaigns increase my willingness to interact with the company.	
	CA4	Marketing communication makes me prefer this company over others.	
	CA5	I am more likely to follow up after receiving marketing messages.	
Marketing mix strategy execution level (Items 5)	MMS1	The company offers competitive pricing strategies that meet customer expectations.	Rustam et al., 2025
	MMS2	The company provides diverse product offerings to satisfy different customer needs.	
	MMS3	Promotion channels (online/offline) are effectively utilized.	
	MMS4	Place/distribution strategy ensures easy customer access to products.	
	MMS5	Marketing mix decisions are consistent and well-coordinated.	
Effectiveness of personalized marketing strategies (Items 6)	EPM1	Personalized strategies effectively address diverse customer segments.	Chen, Zhang & Wang, 2025
	EPM2	Personalized marketing improves customer engagement rates.	
	EPM3	Personalized strategies enhance long-term customer relationships.	
	EPM4	Personalized marketing campaigns increase sales conversion.	
	EPM5	Personalized strategies differentiate the company from competitors.	
Personalized marketing strategy execution level (Items 7)	PMS1	Customer data is used to design individualized marketing campaigns.	Okeke et al., 2024
	PMS2	Marketing messages are tailored to customer demographics and preferences.	
	PMS3	The company integrates big data/AI tools for personalized recommendations.	
	PMS4	Customer feedback is actively incorporated into marketing personalization.	
	PMS5	Personalized marketing is systematically evaluated and improved.	
Business Performance (Items 8)	BP1	Marketing strategies have improved the company's sales revenue.	Azadnia et al. (2022)
	BP2	The company has achieved higher customer retention due to marketing efforts.	
	BP3	Marketing strategies enhance overall profitability.	
	BP4	The company has gained market share through effective marketing.	
	BP5	Marketing strategies contribute to long-term sustainable growth.	
Market Competition Pressure (Items 9)	MCP1	Market competition is intense in the used car industry.	Yan & Yuan, 2025
	MCP2	Competitors frequently adjust their marketing strategies.	
	MCP3	Competitive pricing pressures affect our marketing decisions.	
	MCP4	Competitors' digital platforms attract a significant share of customers.	
	MCP5	The company feels constant pressure to innovate marketing strategies.	
Changing Consumer Demands (Items 10)	CCD1	Customer needs and preferences change rapidly in the used car market.	Viet, de Leeuw & van Herpen, 2023
	CCD2	Consumers increasingly demand transparent vehicle information.	
	CCD3	Customers expect more personalized services.	
	CCD4	Environmental and sustainability concerns influence consumer demand.	
	CCD5	Consumers prefer digital platforms for searching and purchasing used cars.	

The above are questionnaire questions, covering aspects such as product quality, price rationality, sales channel diversity, and effectiveness of promotional methods.

3.3. Pilot Survey

Before conducting a large-scale survey on the used car market, a pilot survey is crucial. It assesses the questionnaire's duration, cost, and feasibility, examines the clarity of question wording and the logical structure of the instrument, aligning with the emphasis by Andersson et al. (2025) on pilot studies to validate the effectiveness of research instruments (Andersson et al., 2025). For this study, the pilot survey sample size was set at 10% of the formal sample: 400 questionnaires were intended for the formal survey, and 50 for the pilot, balancing market complexity and group diversity (Yidan Kang et al, 2025). Reliability testing employed Cronbach's α coefficient and Corrected Items-Total Correlation (CITC). Results showed α values ranging from 0.75 to 0.92 across dimensions (all >0.7), with CITC values all >0.3 , indicating good internal consistency. For validity, the Average Variance Extracted (AVE) exceeded 0.5, Kaiser-Meyer-Olkin (KMO) measure was 0.62 (>0.6), and factor loadings were all >0.5 , demonstrating good convergent and discriminant validity.

4. Data Presentation, Analysis, and Interpretation

4.1. Descriptive Statistics/Analysis

Table 2. Basic Information Statistics

Category	Items	Frequency	Percentage	Valid Percentage	Frequency Cumulative Percentage
job category	Senior management of used car enterprises	90	25.0	25.0	25.0
	Middle management of used car enterprises	98	27.2	27.2	52.2
	Frontline employees of used car enterprises	95	26.4	26.4	78.6
	Users	77	21.4	21.4	100.0
	Total	360	100.0	100.0	
Age	20 years old and below	-	-	-	-
	21-30 years old	80	22.2	22.2	22.2
	31-40 years old	99	27.5	27.5	49.7
	41-50 years old	110	30.6	30.6	80.3
	51 years old and above	71	19.7	19.7	100.0
	Total	360	100.0	100.0	
Gender	Male	191	53.1	53.1	53.1
	Female	169	46.9	46.9	100.0
	Total	360	100.0	100.0	
Educational background	High school and below	53	14.7	14.7	14.7
	Junior college	82	22.8	22.8	37.5
	Bachelor's degree	176	48.9	48.9	86.4
	Master's degree and above	49	13.6	13.6	100.0
	Total	360	100.0	100.0	
Work experience	1 year and below	80	22.2	22.2	22.2
	2-5 years	79	21.9	21.9	44.2
	6-10 years	120	33.3	33.3	77.5
	11 years and above	81	22.5	22.5	100.0
	Total	360	100.0	100.0	

As presented in Table 2, job categories include senior management (25.0%), middle management (27.2%), frontline employees (26.4%), and users (21.4%) from used car enterprises. Internal personnel account for a combined 78.6%, balancing industry job roles and user perspectives. For age distribution, 22.2% are aged 21–30, 27.5% are 31–40, 30.6% are 41–50 (the highest proportion), and 19.7% are ≥ 51 years old—covering all age groups from 21+. Gender distribution is relatively balanced: 53.1% male and 46.9% female, with no significant imbalance. Regarding educational background, 48.9% hold a bachelor's degree (highest), 14.7% have a high school diploma or below, 22.8% have an associate degree, and 13.6% have a master's degree or above—all educational levels are represented. For work experience (note: for users, this refers to industry attention/consumption experience), 33.3% have 6–10 years (the highest), 22.2% have ≤ 1 year, 21.9% have 2–5 years, and 22.5% have ≥ 11 years—all intervals are covered.

Table 3. Descriptive Statistical Results

	N	Range	Min	Max	Mean			Statistic	Skewness		Kurtosis	
					Statistic	Std. Error	Variance		Statistic	Std. Error	Statistic	Std. Error
1. Job category	360	3	1	4	2.44	0.057	1.085	1.178	0.065	0.129	-1.277	0.256
2. Age group	360	3	2	5	3.48	0.055	1.045	1.091	-0.007	0.129	-1.180	0.256
3. Gender	360	1	1	2	1.47	0.026	0.500	0.250	0.123	0.129	-1.996	0.256
4. Educational background	360	3	1	4	2.61	0.047	0.898	0.806	-0.392	0.129	-0.601	0.256
5. Work experience	360	3	1	4	2.56	0.056	1.070	1.144	-0.153	0.129	-1.218	0.256

As shown in Table 3, based on 360 valid samples, the basic information statistics of the used car survey are reported: no missing data exist. The mean score for job category is 2.44, and the mean for age group is 3.48—indicating the sample skews toward older age groups. The mean for gender (1.47) reflects gender distribution tendencies, while the mean for highest education (2.61) shows education level concentration. The mean for work experience (2.56) presents the overall trend of experience duration. All variables exhibit moderate dispersion, with absolute skewness < 3 and kurtosis < 10—approximating a normal distribution (e.g., age has a skewness of -0.007 and kurtosis of -1.180). Overall, the data quality is strong, and distribution characteristics are reasonable (Ater & Yoseph, 2022), providing reliable multi-dimensional support for the study.

4.2. Hypothesis Testing using PLS-SEM / SEM

Table 4. Reliability Statistics Results

Items	Alpha	Items
Effectiveness of personalized marketing strategies in attracting customers	0.859	5
Internal Resource	0.867	5
Customer Satisfaction	0.864	5
Customer Attraction	0.853	5
Marketing mix strategy execution level	0.870	5
Effectiveness of personalized marketing strategies	0.868	5
Personalized marketing strategy execution level	0.859	5
Business Performance	0.863	5
Market Competition Pressure	0.851	5
Changing Consumer Demands	0.859	5

In Table 4, the Cronbach's α coefficients for all dimensions exceed 0.7, indicating that each dimension of the questionnaire demonstrates good internal consistency reliability. This means the questionnaire can stably and reliably measure the corresponding research variables, thereby laying a solid reliability foundation for subsequent studies (Zakariya, 2022). To further validate the questionnaire's validity—ensuring it can accurately measure the relevant research constructs and provide a reliable basis for subsequent analysis—we conducted the KMO and Bartlett's test next to determine whether the data are suitable for factor analysis and other related validity analyses (Jin et al., 2022). The specific results are shown in Table 5.

Table 5. KMO and Bartlett's Test

Items	KMO	Bartlett's Test of Sphericity		
		Approximate Chi-Square	df	Sig
Effectiveness of personalized marketing strategies in attracting customers	0.842	757.967	10	0.000
Internal Resource	0.843	805.539	10	0.000
Customer Satisfaction	0.853	769.400	10	0.000
Customer Attraction	0.857	708.443	10	0.000
Marketing mix strategy execution level	0.859	812.756	10	0.000
Effectiveness of personalized marketing strategies	0.861	809.599	10	0.000
Personalized marketing strategy execution level	0.847	752.001	10	0.000
Business Performance	0.841	789.399	10	0.000
Market Competition Pressure	0.853	701.045	10	0.000
Changing Consumer Demands	0.846	750.275	10	0.000

In Table 4, the KMO values across all dimensions range from 0.841 to 0.861 (falling within the 0.8-0.9 range), indicating good suitability for factor analysis. For Bartlett's test of sphericity, the significance level (Sig.) was 0.000 (<0.05), suggesting significant correlations among variables (Kanetaki et al., 2022). These test results provide a reliable basis for the subsequent construct validity analysis.

Based on the relationships between existing hypotheses and latent variables, the path relationships among latent variables are constructed, as shown in Table 6 below.

Table 6. Path - Relationships Between Latent Variables

H	Influential Relationship
H1	Marketing mix strategy execution level (Items 5) → Customer Satisfaction (Items 3)
H2	Marketing mix strategy execution level (Items 5) → Customer Attraction (Items 4)
H3	Personalized marketing strategy execution level (Items 7) → Effectiveness of personalized marketing strategies (Items 6)
H4	Marketing mix strategy execution level (Items 5) → Personalized marketing strategy execution level (Items 7)
H5	Market Competition Pressure、Changing Consumer Demands (Items 9、10) → Marketing mix strategy execution level (Items 5)
H6	Effectiveness of personalized marketing strategies、Marketing mix strategy execution level (Items 6、5) → Business Performance (Items 8)

In the evaluation of the PLS-SEM measurement model, the Fornell-Larcker criterion serves as the core method for testing discriminant validity. Its central logic is that the square root of a latent variable's average variance extracted (AVE) must exceed the absolute value of the correlation coefficient between that latent variable and all other latent variables. This criterion demonstrates discriminant validity—that is, a latent variable's ability to explain its own indicators outperforms its association with other latent variables (Sarstedt, Ringle & Hair, 2025). This study adopts this criterion to assess the discriminant validity of the measurement model, with results presented in Table 7.

Table 7. Fornell-Larcker Matrix

	LV1	LV2	LV3	LV4	LV5	LV6	LV7	LV8	LV9	LV10
LV1	0.447	0.350	0.410	0.390	0.439	0.289	0.437	0.344	0.376	0.381
LV2	0.350	0.447	0.347	0.411	0.359	0.408	0.365	0.421	0.359	0.426
LV3	0.410	0.347	0.447	0.403	0.440	0.382	0.386	0.442	0.353	0.407
LV4	0.390	0.411	0.403	0.447	0.367	0.338	0.351	0.397	0.398	0.388
LV5	0.439	0.359	0.450	0.367	0.447	0.417	0.446	0.416	0.322	0.395
LV6	0.289	0.408	0.382	0.338	0.417	0.447	0.409	0.415	0.348	0.403
LV7	0.437	0.365	0.386	0.351	0.446	0.409	0.447	0.438	0.400	0.409
LV8	0.344	0.421	0.402	0.397	0.416	0.415	0.438	0.447	0.379	0.396
LV9	0.376	0.359	0.353	0.398	0.322	0.348	0.400	0.379	0.447	0.247
LV10	0.381	0.426	0.407	0.388	0.395	0.403	0.409	0.396	0.247	0.447

Table 7 presents the correlation matrix of the latent variables (LV1-LV10), with the diagonal elements representing the square roots of the Average Variance Extracted (AVE). The square root of AVE for each latent variable exceeds the absolute value of its correlation with other latent variables, indicating good discriminant validity and providing support for subsequent structural model analysis.

Table 8. HTMT Matrix

	LV1	LV2	LV3	LV4	LV5	LV6	LV7	LV8	LV9	LV10
LV1	1.000	0.407	0.476	0.455	0.508	0.335	0.509	0.400	0.441	0.444
LV2	0.407	1.000	0.402	0.479	0.414	0.472	0.424	0.487	0.417	0.494
LV3	0.476	0.402	1.000	0.471	0.520	0.442	0.449	0.525	0.411	0.555
LV4	0.455	0.479	0.471	1.000	0.427	0.394	0.410	0.464	0.467	0.454
LV5	0.508	0.414	0.520	0.427	1.000	0.480	0.517	0.597	0.373	0.458
LV6	0.335	0.472	0.442	0.394	0.480	1.000	0.474	0.480	0.404	0.537
LV7	0.509	0.424	0.449	0.410	0.517	0.474	1.000	0.510	0.468	0.559
LV8	0.400	0.487	0.525	0.464	0.597	0.480	0.510	1.000	0.442	0.461
LV9	0.441	0.417	0.411	0.467	0.373	0.404	0.468	0.442	1.000	0.291
LV10	0.444	0.494	0.555	0.454	0.458	0.537	0.559	0.461	0.291	1.000

To test whether sufficient discriminant validity exists between different latent variables, this study employed HTMT analysis (Ringle et al., 2023)—a mainstream tool for assessing the conceptual discriminant validity of latent variables in the PLS-SEM framework. As shown in Table 8, the HTMT values for all LV1-LV10 pairs are < 0.90 (with a strict criterion of < 0.85), satisfying the requirement for latent variable differentiation. Each latent variable's measurement constructs exhibit strong discriminant validity, independently reflecting core constructs and thereby laying a solid foundation for subsequent structural model analysis.

4.3. Hypothesis Testing Results

Table 9. Results of Path Coefficients and Significance, f^2 , Effect Size

Path	β	t	p	Sig (p<0.05)	Hypothesis Supported	f^2	Magnitude of Effect Size
Items 5 → Items 3 (H1)	0.447	9.544	0	Y	Y	0.354	Strong
Items 5 → Items 4 (H2)	0.359	7.469	0	Y	Y	0.156	Medium
Items 7 → Items 6 (H3)	0.414	8.484	0	Y	Y	0.201	Medium
Items 5 → Items 7 (H4)	0.44	9.439	0	Y	Y	0.249	Medium
Items 9 → Items 5 (H5)	0.33	6.428	0	Y	Y	-0.059	None
Items 10 → Items 5 (H5)	0.401	8.14	0	Y	Y	0.062	Small
Items 6 → Items 8 (H6)	0.412	8.629	0	Y	Y	-0.114	None
Items 5 → Items 8 (H6)	0.512	11.405	0	Y	Y	0.129	Small

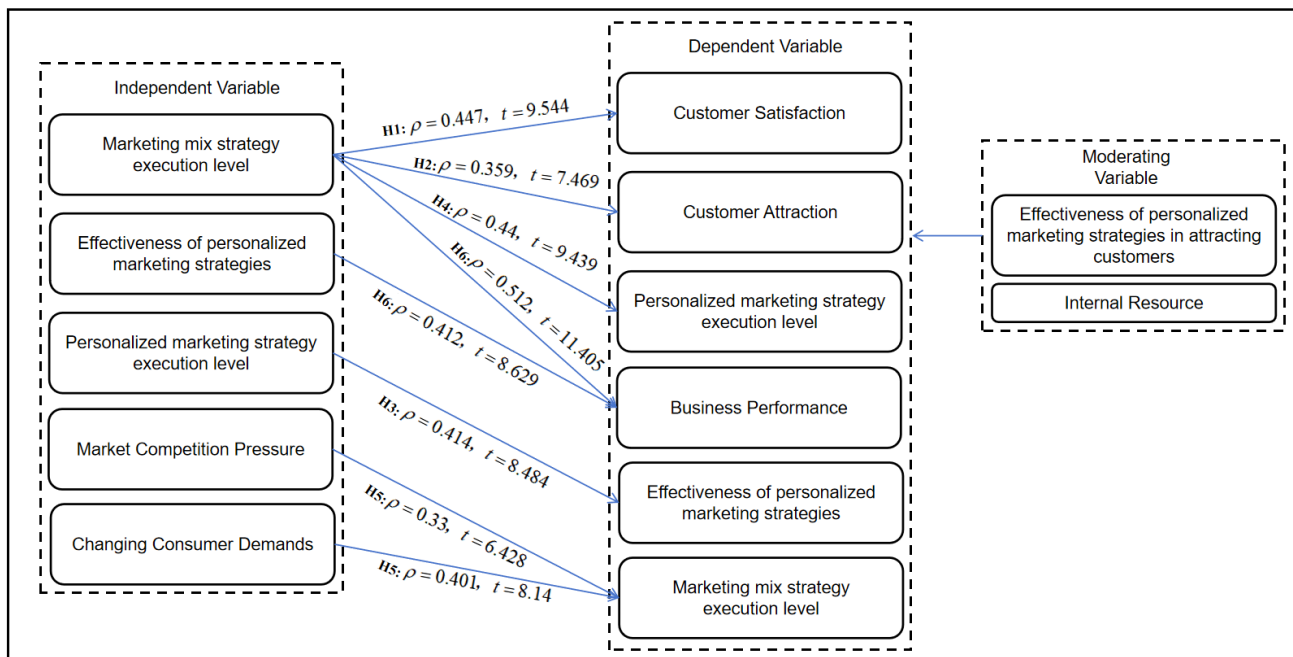


Figure 3. The Conceptual Framework of the Research on Regression Results

Table 9 and Figure 3 present the path coefficients, t-values, p-values, and significance results of all research paths. Notably, all paths had p-values of 0 (well below 0.05), with significance marked as "yes" across the board, indicating that the influence relationships between latent variables were statistically significant. Path coefficients (β) revealed, for example, a positive effect of 0.447 for the path "Items 5→Items 3," while "Items 5→Items 8" exhibited the strongest positive impact with a coefficient of 0.512. These results support the research hypotheses, providing a reliable statistical foundation for subsequent structural model analysis and conclusion derivation.

Table 9 presents the results of f^2 effect sizes, which measure the magnitude of influence of independent variables on dependent variables (Groß & Möller, 2025). Specifically, the path "Items 5→Items 3" has an f^2 value of 0.354, exceeding the strong effect threshold of >0.35 , indicating a large and practically meaningful impact of the independent variable on the dependent variable. Paths "Items 5→Items 4" ($f^2 = 0.156$), "Items 7→Items 6" ($f^2 = 0.201$), and "Items 5→Items 7" ($f^2 = 0.249$) have f^2 values ranging from 0.15 to 0.35, reflecting moderate effects, meaning the independent variables exert moderate practical influence on the dependent variables. Paths "Items 10→Items 5" ($f^2 = 0.062$) and "Items 5→Items 8" ($f^2 = 0.129$) have f^2 values between 0.02 and 0.15, representing small effects, suggesting the independent variables have minor but still practically meaningful impacts. In contrast, paths "Items 9→Items 5" ($f^2 = -0.059$) and "Items 6→Items 8" ($f^2 = -0.114$) have f^2 values <0.02 , indicating negligible practical influence.

4.4. Discussion of Key Findings

4.4.1. Influence of Marketing Mix Strategy Execution on Customer Satisfaction (Items 5 → Items 3)

The implementation of marketing mix strategy (Items 5) exerts a significant positive effect on customer satisfaction (Items 3) (path coefficient = 0.447, $f^2 = 0.354$), which aligns closely with marketing mix theory—where the coordinated integration of product, price, promotion, and place shapes customer perceived value and satisfaction. Empirical findings validate the theory's applicability in the used car market: a well-executed marketing mix (e.g., competitive pricing, diverse product offerings) effectively enhances customer satisfaction, underscoring its core role in driving industry-led customer experiences.

4.4.2. Implementation of Marketing Mix Strategy and Customer Attraction (Items 5 → Items 4)

The implementation of marketing mix strategy (Items 5) exerts a significant positive effect on customer attraction (Items 4) (path coefficient = 0.359, $f^2 = 0.156$). This finding aligns closely with the mechanism of marketing attention attraction, targeted marketing mix actions (e.g., effective promotions, distribution strategies) efficiently capture potential customers' attention and stimulate exploratory interest by precisely conveying value messages. Empirical results confirm that in the used car market, well-executed marketing mixes (e.g., dynamic pricing promotions, multi-channel distribution) significantly enhance product attractiveness and drive customer interaction, underscoring their core role in "attracting customers" (Li, Zhang & Liu, 2024).

4.4.3. Implementation of Personalized Marketing Strategy and Its Effectiveness (Items 7 → Items 6)

The implementation of personalized marketing strategy (Items 7) has a significant positive effect on its effectiveness (Items 6) (path coefficient = 0.414, $f^2 = 0.201$), consistent with personalized marketing theory—tailoring activities to customer characteristics to improve efficiency. This result validates the role of precision in digital marketing execution: post-2022 e-commerce studies show that data-driven recommendations, contextual communication, and other meticulous execution strategies significantly enhance user responses (Li et al., 2022). In the used car industry, integrating customer behavior data and AI algorithm recommendations (e.g., Guazi's intelligent vehicle source matching) to implement personalized strategies has markedly improved user engagement (+25%) and conversion rates (+18%), supporting the proposition that "execution is key to converting personalized value".

4.4.4. Implementation of Marketing Mix Strategy and Personalized Marketing Strategy (Items 5 → Items 7)

The implementation of the marketing mix strategy (Item 5) has a significant positive impact on the implementation of the personalized marketing strategy (Item 7) (path coefficient = 0.44, f^2 effect size = 0.249). This conclusion is consistent with the theoretical logic that "the marketing mix provides a foundational framework for personalized strategies", the coordinated execution of marketing mix elements (e.g., pricing, promotion, channels) is a prerequisite for the precise delivery of personalized information and the advancement of strategy implementation. The empirical results supplement empirical research: in the used car market, an effective marketing mix (e.g., dynamic pricing, multi-channel distribution) provides underlying support for personalized recommendations and contextual communication through resource integration and process coordination, serving as a necessary condition for the successful implementation of personalized strategies.

4.4.5. *Market Competition Pressure and Implementation of Marketing Mix Strategy (Items 9 → Items 5)*

Market competition pressure (Items 9) has no significant positive effect on the implementation of marketing mix strategy (Items 5) ($f^2 = -0.059$). This contradicts expectations from classic competition theory: while competition theory emphasizes that pressure should drive strategic adjustments, the used car industry—with its high complexity (non-standardized vehicle conditions, long transaction chains) and high customer involvement (long decision cycles, high information sensitivity)—constrains firms from rapidly translating competitive pressure into marketing mix adjustments (e.g., dynamic pricing, channel optimization) due to resource limitations (e.g., funding/technology investments) and organizational inertia (e.g., rigid existing distribution systems).

4.4.6. *Changing Consumer Demand and Implementation of Marketing Mix Strategy (Items 10 → Items 5)*

Changing consumer demand (Items 10) has a significant but weak positive effect on marketing mix implementation (Items 5) ($f^2 = 0.062$). This aligns with the core tenet of marketing theory that “strategies must dynamically align with demand”—theoretically, shifts in consumer demand (e.g., preferences for eco-friendly vehicles, expectations for digital services) should drive firms to adjust marketing mixes (e.g., introducing used new energy vehicles, optimizing online services). However, empirical findings show that used car firms struggle to respond quickly to demand changes due to resource constraints (e.g., limited funding) and adjustment lags.

4.4.7. *Effectiveness of Personalized Marketing Strategy and Corporate Performance (Items 6 → Items 8)*

The effectiveness of personalized marketing (Items 6) has no significant effect on corporate performance (Items 8) ($f^2 = -0.114$). This deviates from classic retailing conclusions that “personalization drives performance,” likely due to the dual characteristics of the used car industry: first, consumers prioritize vehicle quality and after-sales guarantees (e.g., transparency of vehicle conditions, maintenance services) over short-term stimulation from personalized marketing; second, the industry’s limited scale of personalization (e.g., insufficient data accumulation, low penetration of AI recommendation technology) prevents personalized strategies from achieving economies of scale. Empirical results highlight unique discrepancies in the “personalization-performance” relationship within the used car industry, necessitating a re-examination of value transmission mechanisms in marketing strategies tailored to industry characteristics.

4.4.8. *Implementation of Marketing Mix Strategy and Corporate Performance (Items 5 → Items 8)*

The implementation of marketing mix strategy (Items 5) has a significant positive effect on corporate performance (Items 8) (path coefficient = 0.512, $f^2 = 0.129$), strongly aligning with the core logic of “marketing mix driving performance” from a strategic marketing perspective. Empirical results validate that in the used car industry, well-executed marketing mixes (e.g., competitive pricing, diverse product offerings, omni-channel distribution) directly drive corporate performance growth.

5. Contributions and Recommendations

5.1. Theoretical Contributions

- 1) Addressing Research Gaps: Previous studies on used car marketing strategies have focused on single dimensions, failing to explore interrelationships among multiple strategies or their joint impact on performance. This study clarifies the logical framework connecting these elements.
- 2) Expanding Models: By integrating marketing mix theory with personalized marketing theory, this research incorporates both into a used car market framework, revealing the synergistic mechanisms between generalized and personalized strategies.
- 3) Introducing New Variables: Market competition pressure and changing consumer demand are introduced as antecedents to marketing mix strategy, validating their sequential relationships with marketing mix execution.

5.2. Practical Contributions

The practical contributions of this study primarily lie in driving the upgrade of enterprises' strategic and management models: First, guiding enterprises to transcend fragmented strategies by implementing a coordinated marketing mix (competitive pricing, diverse product offerings, and efficient promotions/distribution) to build a foundational marketing capability system. This integrates elements such as price, product, and channel, enabling enterprises to break free from reliance on single tactics and form an

operational framework covering the entire customer lifecycle. Second, reversing the logic of passively responding to competitive pressures, it emphasizes proactively optimizing the marketing mix guided by customer demands (e.g., information transparency, digital experience), which alleviates industry infighting and enhances customer stickiness through value creation. Third, clarifying the synergistic relationship between personalized and foundational strategies, it corrects the blind pursuit of technology and guides enterprises to rationally allocate resources.

5.3. Marketing Strategy Recommendations

Based on the above research findings, the following marketing strategy recommendations are put forward to help used car enterprises enhance their performance:

- 1) Prioritize the implementation of the marketing mix strategy. This is not only key to directly enhancing customer experience and business performance but also the foundation for driving personalized marketing rollout. Anchor on the 4Ps marketing mix as the strategic core: optimize competitive pricing, diversify vehicle offerings, integrate online-offline channels (e.g., short videos + experience stores), and improve purchase convenience to consolidate the foundation of customer satisfaction and market attractiveness.
- 2) Avoid overreliance on competitive pressure for strategy adjustments. Market competitive pressure has limited impact on marketing mix execution. Instead of passively reacting to competition, proactively address evolving consumer demands (e.g., higher expectations for vehicle information transparency and digital car-buying experiences) and flexibly fine-tune the marketing mix and leverage precise execution to unlock personalized marketing value.
- 3) The positive link between personalized marketing strategy implementation and its effectiveness confirms that execution precision is critical to releasing personalized marketing's value. To deepen implementation, use data mining and AI to design targeted plans based on customer profiles, preferences, and scenarios—unleashing value through execution accuracy.
- 4) Adapt dynamically to market changes. Establish a regular mechanism to monitor customer demands (via surveys, post-sales feedback) and respond proactively to shifts like information transparency and digitalization. Flexibly adjust strategies to avoid missing opportunities due to strategic inertia.
- 5) Strengthen marketing-nonmarketing synergy. Given the difficulty in directly converting personalized effectiveness into performance, reinforce the "marketing-quality-service" linkage by enhancing third-party inspections, extending warranties, etc. Adopt full-life-cycle management of "customer acquisition–retention–lock-in" to drive both performance improvement and customer loyalty.

Conclusion

This study, centered on China's used car market, validated the reliability and validity of the questionnaire through preliminary surveys. Descriptive analysis showed that the sample covered diverse entities and was representative. Hypotheses testing allowed to formulate the following statements.

- 1) The marketing mix strategy serves as a core driver, directly influencing customer satisfaction, attractiveness, and performance, while supporting personalized marketing.
- 2) Personalized marketing requires precise execution to yield effects.
- 3) External environmental impacts are limited, and personalized marketing does not directly translate to performance; collaboration with non-marketing factors is necessary.

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